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Which came first? ... see p. 1



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Agricultural Economics Research

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In the scientific community, everyone's position is sovereign, according to Michael Polanyi; science dissolves under the control of hierarchical authority. In his introduction to the latest edition of *Science, Faith, and Society*, Polanyi makes it clear that his idea applies to "economics, sociology, and the humanities" as much as to what we sometimes call the hard sciences. Scientists work under what Polanyi calls a "perpetual tension between discipline and originality." Discipline requires application of accepted rules; originality requires taking actions not determined by rules. "From beginning to end [the scientist] is himself the ultimate judge in deciding each consecutive step in the inquiry." The scientific community would dissolve instantly, according to Polanyi, if independence and the opportunity for originality and personal judgment were to end.

The articles in this issue illustrate originality and judgment in USDA's economics research. The authors examine a new operational definition of an old concept, a new admixture of research procedures, a new

procedure for assessing change, and a new data source.

The idea of causality has attracted much attention over the centuries in philosophy and science. Side-stepping the traditional arguments, Bishop uses an operational definition of causality that has been in the literature for only a decade. The idea centers on an interpretation of lead variables in regression analysis in combination with conventional lag variables. Bishop's statistical tests find, for example, that the money supply is causally related to a change in the general price level.

Demand and supply functions are notoriously hard to identify, given the availability of relevant data and the present state of the econometric art. Lamm avoids this identification problem by using what he calls a pseudodata set which is generated by a stochastic process through a linear programming model. His supply function, estimated from this pseudodata set, is then mixed with a set of demand relationships estimated by the usual econometric techniques.

Market structures are known to change over time, yet researchers

setting up models of the demand and price for agricultural commodities tend to assume structural stability so that parameters can be estimated more easily. Hassan and Johnson examine two statistical tests which have been proposed for assessing structural change. Their study of time series data for Canada suggests most meat demand functions tend to be structurally stable but that an important structural change in 1969 in the beef market could introduce difficulties into models which, *a priori*, assume there was no such change.

Time series data are frequently too short, so a discovery that untapped but potentially useful observations are available on prices and quantities is always welcome. Tomek shows that using USDA's forecasts of crop production and corresponding futures prices—a procedure which provides up to five price-quantity observations per year—conveys more information about the demand for a crop than the single, final crop estimate and final price.

CLARK EDWARDS

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The Construction and Use of Causality Tests

By Robert V. Bishop*

INTRODUCTION

The researcher, in setting up a research approach to the subject matter, must specify the appropriate cause and effect relationship based on theoretical grounds. In the simple relationship Y equals $f(X)$ estimated by ordinary least squares, the researcher assumes that changes in Y (the dependent or endogenous variable) are caused by changes in X (the independent or exogenous) variable. This relationship represents the traditional Aristotelian view of causality.

Granger (7) has provided a definition of causality that lends itself to empirical testing procedures, and that allows the researcher to examine the underlying causal structure among economic time series.¹ He assumes that (1) the variables being tested result from stochastic (rather than deterministic) processes, (2) the series are stationary,² and (3) the future cannot cause the past. The last assumption has given rise to some controversy since time plays a central role in his definition. Cause and effect must, by definition, be temporally separated.

If we examine an information set of two variables X and Y , the possible causal orderings are:

- (1) X causes Y ($X \Rightarrow Y$),
- (2) Y causes X ($Y \Rightarrow X$),
- (3) X and Y cause each other (bidirectionally) ($X \Leftrightarrow Y$),
- (4) no causal relationship exists.

The purpose of this article is to describe an empirical test that can be used to identify the appropriate causal ordering—(1) through (4) above—in the bivariate information set under consideration. I give specific examples of agricultural research to which this test could be applied as a brief list of potential applications.

The relationship between producer price of a commodity and the price of that good at the wholesale or retail level exemplifies a situation in which this test is well suited. Some assume that changes in prices at the farm level lead to changes in wholesale and/or retail prices. Others assume that, because of the nature of the food processing industry, no strong relationship exists between producer and retail food prices. The technique I present represents one avenue for empirically examining such structures.

Another interesting application involves the question of price trans-

mission among countries. If one defines a world price as one that "drives" other prices, one could determine which price, if any, is the world price, as well as discern whether a causal structure exists (whether prices are transmitted among regions).

Other possible applications include: testing for the effect of set-aside programs on market price; and examining the appropriateness of single-equation estimation techniques for demand or supply functions.

GRANGER'S DEFINITION OF CAUSALITY

If the true causal structure is $Y \Rightarrow X$, the researcher should regress X on Y (X equals $f(Y)$). The importance of the appropriate relationship is immediately seen when one introduces a distributed-lag structure into the model:

$$(X_t = b_0 + \sum_{i=1}^n b_i Y_{t-i}),$$

where X is hypothesized to be a function of past values of Y (the independent variable). This definition provides the researcher with the appropriate structural specification; whether the model under test is captured properly by a single estimating equation or by a system of equations. For example, if the appropriate relationship is $Y \Leftrightarrow X$ (Y and X cause each other bidirectionally), the system is simultaneous and, consequently, some system estimation technique is indicated. If the true relationship is $X \Rightarrow Y$ and a system estimation technique is employed, the results would be markedly similar to a single-

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¹Italicized numbers in parentheses refer to items in References at the end of this article.

²A stationary series can be defined as one in which the stochastic properties do not vary over time. For example, if Y is stationary, then $E(Y_t)$ equals $E(Y_{t+m})$; the mean of the series does not change over time. The variance and covariance of the stationary series also are invariant with time. For a discussion of the assumptions, see Granger (7, p. 428).

Granger has provided a definition of causality that lends itself to empirical testing procedures, and that allows the researcher to examine the underlying causal structure among economic time series.

equation estimation of Y equals $f(X)$. This result is important, as one criticism of system estimation is that the results are similar and therefore the additional computational costs are not justified. However, given the potentially serious problem with simultaneous equations bias when a simultaneous system is estimated by a single-equation method, it is important to ascertain the causal structure.

The formal definition of causality is:

If $\sigma^2(X|\bar{U}) < \sigma^2(X|\bar{U}-\bar{Y})$, we say that Y is causing X , denoted by $Y_t \Rightarrow X_t$. We say Y_t is causing X_t if we are better able to predict X_t using all available information than if information apart from Y_t has been used (7, p. 428).

In other words, the variable Y causes X with respect to the information set ($\bar{U}$), which includes both X and Y , if, and only if, the present value of X is predicted better by using the past values of Y than if these values had not been used (denoted above as $\bar{U}-Y$).

EMPIRICAL TESTING FOR CAUSAL ORDERING

Sims provides the empirical content needed for the application of causality tests based on Granger's criterion. The test he prepared is:

If and only if causality runs one way from current and past values of some list of exogenous variables to a given endogenous variable, then in regression of the endogenous variable on past, current, and future values of the exogenous variables, the future values of the exogenous variables should have zero coefficients (21, p. 541).

Using the information set containing observations on X and Y , we can conduct Sims' test as follows:

Regress Y on past and future values of X , taking account by generalized least squares or prefiltering of the serial correlation in $w(t)$ (the regression residuals). Then if causality runs from X to Y only, future values of X in the regression should have coefficients insignificantly different from zero as a group (21, p. 544).

The prefiltering referred to here is accomplished by creating a vector of observations through the use of the following transformation on both variables:

$$\begin{aligned} &(\ln X(t) - 1.5 \ln X(t-1) \\ &+ 0.5625 \ln X(t-2)) \end{aligned} \quad (1)$$

which is a second-order filter of the general form:

$$(1 - kL)^2$$

where:

k is set equal to 0.75, and
 L is the lag operator.³

Sim's choice of $k = 0.75$ in the general form was based on the observation that this filter "approximately flattens the spectral density function of most economic time series, and

the hope was that regression residuals would be very nearly white noise with this prefiltering."⁴ The filtering (or prefiltering) referred to above is an empirical device used to remove the autocorrelation in the error structure. An example of a simple first-order filter is first differencing $(1-L)$; another is the filter used in the Cochrane-Orcutt iterative technique $(1-\bar{\rho}L)$.

In assessing the effectiveness of the prefilter, Sims warns that one should not rely on the Durbin-Watson statistic. He notes that the Durbin-Watson statistic fails to test adequately for this because autocorrelation remaining after the application of this filter would most likely be of an order *greater* than one. A method of testing for higher orders of autocorrelation in the error structure is to perform a general autoregression on the residuals. Finding statistically significant coefficients leads to the rejection of the null hypothesis of no autocorrelation.⁵

If the prefiltering fails to remove the serial correlation adequately, the effect can be viewed as one of "spurious regression," as discussed by Granger and Newbold (9). The estimates of the coefficients will be consistent, but there will be bias in the estimates of their variances. If this bias results in the underestima-

³The lag operator (L^n) defines the number of periods (n) that the observations are lagged in transforming the data series. For example, the transformation $(1-L)$ of the series Z_t is $Z_t^* = Z_t - Z_{t-1}$ (where Z_t^* is the transformed series). The power to which (L) is raised defines the exact number of included lags: $(1+L-L^2)$ Z_t implies a transformation of $Z_t^* = Z_t + Z_{t-1} - Z_{t-2}$.

⁴Mehra (13) disputes this observation, stating that the filter that flattens the spectral density function of $Y = f(X)$ will not necessarily do so for $X = (Y)$.

⁵Significant coefficients on lags greater than 2 identify the presence of autocorrelation of order greater than 2. In this case, a filter of higher order is needed to purge the autocorrelation. If the coefficient on e_{t-3} is significant, a third-order filter is needed (such as $(1-kL)^3$).

tion of the variance (downward bias), the "t" and "F" statistics, as well as the R^2 , will be biased upwards. This bias could lead to the "identification" of nonexistent causal relationships.

Note that if the bias is in the opposite direction, the significance of the relationship will be underestimated; thus, the test would fail to identify an existing causal relationship. The filter must remove as much of the autocorrelation in the regression residuals of the transformed series as possible. Note that the filter does not necessarily have to remove the autocorrelation present in the transformed input series themselves (of the bivariate system under test) (15, pp. 22-23).

Sims warns that the lag distribution should not be subject to prior smoothness constraints (such as Almon's, Koyck's, or rational lag restrictions) but be kept "generous." Premature truncation of the lag distribution can also lead to incorrect identification of causal ordering in the system under test. At the same time, one must recognize that the inclusion of additional leads and lags of the "independent" variable can lead to problems of multicollinearity in the variables. The lead and lag structure must be such that the hypothesized relationship is captured. For example, if X causes Y with a lag of 6 months, lags covering at least that period of time must be included.

Using the prefiltered series, Sims examined the direction of causality between money and gross national product. Sims states that:

the test applied in this paper shows (that) no feedback from Y to X is a necessary condition for it to be reasonable to interpret a

distributed lag regression of Y on current and past X as a causal relation or to apply any of the common estimation methods involving the use of lagged dependent variables or corrections for serial correlation. Hence the most conservative way to state the results for money and income is that they show it to be unreasonable to interpret a least squares lag distribution for money on GNP as a causal relation, and that they provide no grounds for asserting that distributed lag regressions of GNP on money do not yield estimates of a causal relation. It is natural, and I believe appropriate, to phrase the result more positively: the data verify the null hypothesis that distributed lag regressions of GNP on money have a causal interpretation (21, pp. 541-542).

Sims rejects the null hypothesis that "distributed lag regressions of GNP on money do not yield estimates of a causal relation." The "stronger" statement arises from the acceptance of the alternate hypothesis that: "distributed lag regressions of GNP on money have a causal interpretation."

Mehra suggests that the choice of an *ad hoc* filter is not necessarily appropriate, nor is the same filter necessarily appropriate when the regressor and regressand are reversed in the estimation procedure (13). He suggests that the following procedure be used to define empirically a filter which removes the autocorrelation from the residuals for the causality tests. This filter, assumed to be of the second order, has the same general form as the one presented by Sims (21) $[(1-kL)^2]$. However, the value of k is not defined ahead of time but is chosen empirically to eliminate the presence of serial correlation. The

procedure to determine the appropriate value of k is as follows:

Form an appropriate specification of the two-sided lag relation under test, and include a linear trend term and seasonal dummies. Use some *ad hoc* filter (he suggests $k=0.75$) to prefilter the variables. Apply OLS to estimate the lag profile.

Examine the autoregressive properties of the residuals by performing the following autoregression (where $e(t)$ is defined as the residual in period (t)):

$$e(t) = B(1) e(t-1) + B(2) e(t-2)$$

If the preceding autoregression indicates that the error structure is uncorrelated, the choice of the *ad hoc* value of k is appropriate for the specification under test (B(1) and B(2) are statistically insignificant).

If the autoregression indicates the presence of some serial correlation, the value of k is changed and the procedure is repeated (13, pp. 1,230-1,231).

The proper filter for the function of Y equals $f(X)$, is not necessarily the same as the filter for X equals $f'(Y)$.

Once the appropriate value of k is chosen for both specifications, the transformations on the raw data series are performed as follows:

$$Y_t^* = Y_t - 2kY_{t-1} + k^2Y_{t-2} \quad (2)$$

and

$$X_t^* = X_t - 2k'X_{t-1} + k'^2X_{t-2} \quad (3)$$

If expectations of future movements in one variable affect the movements of another variable, the direction of causality is affected.

One estimating equation for testing the null hypothesis that X causes Y ($X \Rightarrow Y$) is:

$$Y_t^* = a_0 + \sum_{s=-i}^m b_s X_{t-s}^* + \sum_{j=1}^3 c_j D_j + f_t LT + v_t \quad (4)$$

where:

$i = 4$ and $m = 8$; D_1, D_2 , and D_3 are seasonal dummies; LT is a linear trend term.

If leading values of $X^*(X_{t-s}^*)$ where $s < 0$ are significantly different from zero as a group, we fail to reject the null hypothesis that Y causes X. In this instance, future values of X are significant in explaining current Y. Note that this is a necessary but not sufficient condition for establishing a unidirectional causal link from Y to X as for a unidirectional system we need $Y \Rightarrow X$ and $X \Rightarrow Y$. Therefore, for sufficiency, X must not cause Y ($X \nRightarrow Y$). If the second condition is not met, X also causes Y and a bidirectional feedback system has been identified.

One limiting factor in the application of such tests is that many observations are lost through leading and lagging. Realistically, one must provide a sufficient number of leads and lags to encompass the hypothesized temporal distance between cause and effect. The examples here suggest eight lags and four leads. These are for quarterly data and seem reasonable. For annual data, they are

excessive. One can use different specifications of lead and lag length and note the sensitivity of the model to the chosen truncation.

The series are transformed using the appropriate values of k (see equations (2) and (3) above). Equation (5) is defined using the identical form of (4) but interchanging the dependent and independent variables:

$$X_t^* = A_0 + \sum_{s=-i}^m B_s Y_{t-s}^* + \sum_{j=1}^3 C_j D_j + F_t LT + V_t \quad (5)$$

where all variables are as described for (4) above.

To examine the causal structure between X and Y given the possible causal outcomes of: (1) $Y \Rightarrow X$; (2) $X \Rightarrow Y$; (3) $X \nRightarrow Y$; and (4) no causal relationship, we estimated the following relationships:

- (A) $Y_t = f(X_t: 8 \text{ past, present, 4 future})$,
- (B) $Y_t = f(X_t: 8 \text{ past, present})$,
- (C) $X_t = f(Y_t: 8 \text{ past, present, 4 future})$,
- (D) $X_t = f(Y_t: 8 \text{ past, present})$.

where (A) - (D) also include seasonal dummies and linear trend terms. An F test is constructed as:

$$F = \frac{SSE_r - SSE_u / (q-p)}{SSE_u / (n-q)}$$

where the terms are defined as follows:

SSE_r is the sum of squared resid-

uals in regression (B),

SSE_u is the sum of squared residuals in regression (A),

q equals the number of parameters estimated in regression (A),

p is the number of parameters estimated in (B), and

n equals the number of observations.

Under the null hypothesis that the four future coefficients are insignificantly different from zero as a group in the F test performed above, the computed F is compared with the table F for the appropriate degrees of freedom at the desired level of significance. If the null hypothesis is rejected for Y on X, future X is significant in explaining current Y. In this case, a Granger-Causal ordering is established from Y to X. The test is repeated for X on Y.

Table 1 clarifies these regressions (3, pp. 34-43). M represents the narrowly defined money stock (M_1) and CPI refers to the Consumer Price Index. Fourth-order autoregressions of the residuals of the estimating equations in table 1 yielded insignificant coefficients on all terms. From table 2, a unidirectional causal link is found from money to prices in 1951-76.

LIMITATIONS AND CAVEATS

Sims noted that if expectations of future movements in one variable affect the movements of another variable, the direction of causality is affected (21). He does qualify this somewhat by stating that if this were the case, a unidirectional system would more likely appear bidirec-

Table 1.—Results of regressions used in the causality test

Regression	DW	F	R ²	SEE
CPI = $f(M, \text{past})^1$	1.95	1.57	0.19	0.00431
CPI = $f(M, 8 \text{ past}, 4 \text{ future})^1$	2.03	1.82	.27	.00419
M = $f(\text{CPI}, 8 \text{ past})^2$	1.85	14.06	.66	.00470
M = $f(\text{CPI}, 8 \text{ past}, 4 \text{ future})^2$	1.97	12.87	.71	.00450

Note: All regressions contained the current value of the regressor, seasonal dummies, and a linear trend term.

¹ Prices on money used a complex fourth-order filter $[(1-kL)^4]$ because of higher order autocorrelation in the error structure. For construction of this complex filter, see (3, pp. 34-37). ² Money on prices used a second-order filter.

Table 2.—F test on four future coefficients¹

Causal pattern	Regression	F (4,83)
M⇒CPI	M on CPI	² 5.090
CPI⇒M	CPI on M	2.30

¹ M on CPI utilized second-order filter; CPI on M used a fourth-order filter. ² Significant at the 0.05 level.

tional than a bidirectional system appearing unidirectional. Pierce warns that if measurement error or added noise (including seasonality when it is so viewed) are present, the test is not appropriate:

If $X=X(1) + X(2)$ and $Y=Y(1) + Y(2)$, all components being stationary, it may well be that different causality events will hold for $X(1)$ and $Y(1)$ than for X and Y (15, pp. 41-42).

If we assume that X (or Y) is the measured value of a series, $X(1)$ (or $Y(1)$) the true value, and $X(2)$ (or $Y(2)$) the measurement error, we can see easily the problem associated with

the interpretation of the causality test. Sims suggests that if the measurement error is large in one variable and not in the other, the other would be more likely to appear exogenous if the variable with the larger error appears as dependent.⁶

Pierce and Haugh offer a warning in the special case where one variable is being "controlled:"

Under some fairly general conditions in which an independent variable can be controlled or influenced by someone who does so on the basis of movements in a dependent variable Y , the feedback control rule or reaction function can dominate the empirical relationship. This would result in reporting that Y causes X (the independent variable) . . . in cases where the structural relationship is one of causation only from X to Y (15, p. 42).

⁶ Sims (20, p. 35) warns that he did not say that the presence of measurement error makes spurious causal orderings likely. He only emphasized that, under certain special structures possible in measurement errors, spurious causal orderings could be generated.

Ando claims that using pair-wise ordering in Granger's sense of it does not capture the true, more complicated relationship underlying the variables (1). The other researchers mentioned use only two variables in the universe (more with inclusion of trend and seasonal dummies). Thus, Ando questions the validity of those tests.⁷

Sargent counters by stating that if variables have been omitted in the specifications, one would be more likely to identify a feedback structure than a unidirectional system as Sims did (17, p. 217). Sargent thus implies that the identification of a "feedback system" is subject to Ando's criticism and may be an erroneous identification but a unidirectional flow is, in general, not subject to this criticism. Sargent also noted that the real value of Sims' test is its ability to test for the appropriate *a priori* restrictions on statistical exogeneity.

CONCLUSION

The meaning of causality has presented problems over the years as is evidenced by the large number of definitions given it.⁸ The complexity of the concept notwithstanding, the most fundamental relationships in economics are built upon assumed causal structures. Every time we run a regression of one variable (A) on another (B) we are *assuming* a causal structure from B to A exists. The

⁷ Pierce has developed a multivariate methodology to test for the causal relationship among many variables.

⁸ See Zellner (22), pp. 62-63 for a brief summary of several definitions of causality.

technique described above presents a method of empirically testing the hypothesis that B does cause A rather than making the assumption that it does. The definition of causality described by Granger is workable in that one can test statistically for exogeneity (given the assumptions listed above), while other definitions do not lend themselves to empirical testing procedures.

Tests of this nature have been used in many ways; to examine the wage-lag hypothesis, migration patterns, cost-push versus demand-pull inflation, to test the Rational Expectations hypothesis and relationships between money and income, as well as money and prices—to name a few. Research in agricultural economics provides a fertile area for tests of this type. Properly used, this methodology can contribute significantly to the understanding and examination of the theoretical underpinnings relating important economic variables.

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Effects of Control on the Domestic Peanut Industry

By R. McFall Lamm, Jr.*

INTRODUCTION

The domestic peanut industry has operated for over 40 years under Government control programs. Their principal objective, embodied in legislative acts, has been to maintain the net income of peanut producers at "satisfactory" levels. "Satisfactory," however, has not been clearly defined by the Congress. Instead of designating targets for producer income, legislators have established price support levels and acreage quotas and have given limited consideration to long-run consequences. The results have been higher net incomes to peanut producers, large program costs, and the accumulation of large peanut stocks.

There has been much debate recently over whether net social benefits accrue from peanut control programs. If income transfer is the only objective of control, perhaps it could be accomplished more efficiently under an alternative program.

An obvious alternative program is one with no controls—production levels and price are determined in the free market. This alternative has traditionally been the standard of comparison for evaluating the effects of controls. Song, Franzmann, and Mead (16), and Fleming and White (2) have attempted to derive free market, price-quantity time paths for the peanut industry using annual econo-

The domestic peanut industry has operated under Government programs for over 40 years, programs designed primarily to increase producers' income. The author evaluates effects of these controls on the industry, and provides an estimate of their indirect costs to consumers.

The major novelty of the annual econometric model of the industry used in the analysis is the methodology for estimating the supply function. Instead of actual time-series data, the supply function is estimated from pseudodata generated by linear programming models.

Keywords

*Peanut production
Government policy
Linear programming
Econometric model*

metric models.¹ They limit their approach to the demand side of the market. Studies by Marshall, Little, and Kline (10), and by Nieuwoudt, Bullock, and Mathia (12) use linear programming models to develop the supply side but regard demand side variables as determined exogenously. A complete treatment of the problem requires that demand and supply be determined endogenously.

This article reports on the effects of controls on the domestic peanut industry from 1952 through 1976, and it presents an approximation of the indirect costs (to consumers) of control programs. An annual econometric model is developed in which demand and supply are endogenous. The major novelty of the study is the methodology used to estimate the supply function; pseudodata generated by linear programming are used rather than actual time-series data.

¹ Italicized numbers in parentheses refer to items in References at the end of this article.

The econometric model of the peanut industry, incorporating the pseudosupply function, consists of 14 linear equations, 9 of which are behavioral relations. The model generates price-quantity time paths for peanuts and three major peanut products: peanut oil, peanut meal, and edible peanuts. Linearity and expected profit maximization are underlying assumptions.

EVOLUTION OF DOMESTIC PEANUT PROGRAMS

Peanuts were added in 1934 to the list of commodities covered by the Agricultural Adjustment Act. This addition placed the market for peanuts in the United States under numerous Government controls. Initial legislation gave the Secretary of Agriculture authority to determine the quantity to be produced each year and established marketing quotas. After 1941, producers were restricted to marketing only those peanuts grown on allotted acreage. Specific price support levels, to be announced prior to planting, were authorized beginning in 1941.

Controls were abandoned during World War II, except for minimum price guarantees of 90 percent of parity. A new Agricultural Adjustment Act reintroduced controls in 1949. This act required the Secretary of Agriculture to announce the price support level, between 75 percent and 90 percent of parity, prior to the beginning of the peanut marketing season, and it established a minimum national allotment of 1,610,000 acres. Acreage restrictions and price supports, basic features of post-war

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The major novelty of the study is the methodology used to estimate the supply function; pseudodata generated by linear programming are used rather than actual time-series data.

peanut control programs, have continued to the present day.²

Virtually no revision was made in peanut control programs after 1949 until the passage of the Food and Agriculture Act in 1977. The new program retained price supports and acreage allotments, and imposed poundage quotas at the State and farm level. Two support prices were applied—one for peanuts produced within poundage quotas and the other for peanuts exceeding poundage quotas but satisfying the acreage quota. In addition, instead of receiving support prices, producers were given the option of contracting with peanut processors at a single price.³

Table 1 presents the levels of control variables, and actual harvested acreage, production, price, and Commodity Credit Corporation (CCC) losses for peanuts from 1935 to 1976. The control variables are as follows: acreage allotments, marketing quotas, price supports, and CCC acquisitions. Acreage allotments and support prices were active control variables over much of the study period. Marketing quotas, however, have not been active controls but have been gradually adjusted upwards to approximate actual production on allotted acreage. Similarly, the control variable, CCC

acquisitions, is not active but depends functionally on acreage allotment, support price, and production.

Peanut prices and acreage have varied little over time, especially since 1949, principally because of control. The level of CCC losses, which has varied, represents a direct cost of imposing control. Total CCC losses from 1935 to 1976 were \$959 million, or \$1.609 billion in constant 1976 dollars. This loss represents the largest per unit subsidy for any major crop.

MODEL SPECIFICATION

The basic objective of the model specification is to allow a determination of free-market, price-quantity time paths that would result if no controls had been imposed on the peanut industry. These paths can be compared with actual price-quantity time paths to determine the net effects of control.

The cost of control programs is represented by: (1) direct costs—CCC losses incurred in buying and selling commodities for support operations, and program administrative expenses; (2) indirect costs arising when consumers pay higher prices for finished products as a consequence of controls; (3) and welfare costs that accrue when the sum of change in producers' and consumers' surpluses due to controls is negative. Any of these costs may become benefits, of course, although generally this has not happened in domestic agricultural control programs.

It might be argued that the indirect costs of control programs are not generally costs but benefits—the Government supports raw agricultural

prices which encourages production, which leads to lower food prices through outward shifts in supply. If the Government supported commodity prices through direct purchases, and sold to food processors at market prices, then this argument might be valid. However, Government sales of commodities have generally been carried out through discriminatory disposal programs. Instead of being sold to food processors, commodities have been sold for restricted uses, donated, or sold at reduced prices to other countries. For peanuts, the Government has discriminated between edible peanut markets and the crushing market—edible peanuts have been contracted for sale by the Government for crushing. This policy implies higher prices for edible peanuts and positive indirect costs.

The standard approach for approximating free-market time paths is to construct an econometric model, as Heien (5) and others have done. Typically, both demand and supply side representations are included; control variables are exogenous. Stochastic or deterministic simulations are performed with the values of all control variables set equal to zero. Simulated free-market time paths result. Indirect-control costs can be computed based on differences between actual and simulated time paths.

Usefulness of econometric models for measuring indirect control costs depends on the availability of appropriate sample data. It is crucial that controls be applied over only part of the sample period, or that the levels of control variables change frequently, which imparts the necessary variation to allow estimation of parameters. For the domestic peanut indus-

² See Song (16) and Little (8) for a detailed review of the evolution of domestic peanut control programs.

³ As with previous programs, producers' associations continue to act as agents of the Commodity Credit Corporation. Loans are made to farmers at the support price and redeemed when peanuts are harvested and delivered. All peanuts which cannot be sold at prices greater than the support price become the property of the Commodity Credit Corporation. See (18) for a review of the new program.

Table 1—Levels of control variables, acreage, production, price, and CCC losses, 1935-76

Year	Control level				Actual			
	Acreage allotment	Marketing quota	Support price	CCC acquisitions	Acreage	Production	Price	CCC loss
	<i>1,000</i>	<i>Million pounds</i>	<i>Cents/pound</i>	<i>Million pounds</i>	<i>1,000</i>	<i>Million pounds</i>	<i>Cents/pound</i>	<i>Million dollars</i>
1935	N.A.	N.A.	N.A.	73	1,497	1,153	3.1	0.3
1936	N.A.	N.A.	N.A.	0	1,660	1,260	3.7	0
1937	N.A.	N.A.	N.A.	166	1,538	1,233	3.3	2.3
1938	1,448	N.A.	N.A.	253	1,692	1,289	3.3	3.3
1939	1,448	N.A.	N.A.	69	1,908	1,213	3.4	.7
1940	1,448	N.A.	N.A.	558	2,052	1,767	3.3	7.9
1941	1,448	N.A.	4.4	378	1,900	1,475	4.7	0
1942	1,610	1,256	6.6	899	3,355	2,193	6.1	0
1943	N.A.	N.A.	7.1	0	3,528	2,176	7.1	0
1944	N.A.	N.A.	7.3	0	3,068	2,081	8.0	0
1945	N.A.	N.A.	7.5	0	3,160	2,042	8.3	0
1946	N.A.	N.A.	8.6	55	3,141	2,038	9.1	-.6
1947	N.A.	N.A.	10.0	528	3,377	2,182	10.1	3.5
1948	N.A.	N.A.	10.8	1,167	3,296	2,336	10.5	25.6
1949	2,629	1,700	10.5	763	2,308	1,865	10.4	39.7
1950	2,000	1,286	10.8	835	2,262	2,035	10.9	17.1
1951	1,889	1,300	11.5	540	1,982	1,659	10.4	9.4
1952	1,706	1,300	12.0	106	1,443	1,356	10.9	4.8
1953	1,679	1,326	11.9	294	1,515	1,574	11.1	14.0
1954	1,610	1,348	12.2	0	1,387	1,008	12.2	0
1955	1,731	1,592	12.2	268	1,669	1,548	11.7	17.1
1956	1,650	1,500	11.4	334	1,384	1,607	11.2	20.2
1957	1,611	1,451	11.1	108	1,481	1,436	10.4	6.1
1958	1,612	1,652	10.7	383	1,516	1,814	10.6	21.2
1959	1,612	1,772	9.7	246	1,435	1,523	9.6	11.4
1960	1,612	1,868	10.1	299	1,395	1,718	10.0	16.7
1961	1,612	1,940	11.0	231	1,398	1,657	10.9	12.1
1962	1,613	2,012	11.1	331	1,400	1,719	11.0	21.2
1963	1,612	2,012	11.2	371	1,396	1,942	11.2	28.3
1964	1,613	2,133	11.2	512	1,397	2,099	11.2	30.5
1965	1,613	2,375	11.2	688	1,438	2,384	11.4	44.3
1966	1,613	2,737	11.4	701	1,421	2,410	11.3	43.8
1967	1,613	2,858	11.4	605	1,404	2,473	11.4	48.2
1968	1,613	2,978	12.0	581	1,438	2,543	11.9	38.8
1969	1,612	3,099	12.4	588	1,456	2,529	12.3	36.0
1970	1,613	3,075	12.8	1,062	1,467	2,979	12.8	66.3
1971	1,613	3,107	13.4	1,175	1,454	3,005	13.6	97.3
1972	1,613	3,268	14.3	1,178	1,486	3,275	14.5	58.0
1973	1,612	3,542	16.4	834	1,496	3,474	16.2	5.0
1974	1,612	3,703	18.3	962	1,472	3,668	17.9	3.0
1975	1,612	3,799	19.7	1,012	1,504	3,857	19.6	111.0
1976	1,612	4,009	20.7	841	1,522	3,751	20.0	102.0

Note: N.A. means not applicable.

The methodology involves linear programming models representing the producer's decision problem, with commodity prices taken as given.

try, prices for peanut products have varied considerably over the years, sufficiently to allow the estimation of demand-side relations. Acreage allotments and price supports have not varied substantially over much of the sample period, however, being virtually constant from 1952 to 1976. The result is that, when a supply function is estimated, peanut production is found to be virtually insensitive to changes in price.

Available sample information does not allow estimation of the supply side of the model. One alternative is to generate a pseudodata set with sufficient variation to allow the estimation of a supply function. The generation of pseudodata has been advocated recently by Griffin (3, 4) in a study of the petroleum industry. It resembles the approach suggested by Shumway and Chang (14) for determining supply functions for major U.S. crops.

The methodology involves linear programming models representing the producer's decision problem, with commodity prices taken as given. Random variation of peanut prices, with other commodity prices at constant levels, results in a schedule of optimal values for peanut production for alternative prices. The supply function can be estimated from this pseudodata set.

THE SUPPLY SIDE

U.S. peanut production is concentrated in three major regions: southeastern Virginia and eastern North Carolina, central Alabama and western Georgia, and central Texas and southern Oklahoma. Linear programming models were constructed to

represent individual producer decisions in each of these regions. The models are simple, incorporating basic crop substitutes for each region, but omitting livestock production activities. Aggregation gives regional output levels, which in turn sum to national output.

Alternative output activities for each decision model include peanut, cotton, and corn production. In addition, soybean production is included as an output activity in Virginia-North Carolina. Input activities include capital, and land used for peanuts or for other crops. These two land classifications allow a resource constraint to be applied to land used for peanut production, which simulates the effects of an acreage allotment. Other constraints are placed on total capital and land availability.

Individual producers in each region are assumed to maximize expected profits $E_{t-1}(f_t)$ subject to resource constraints. Expected profit is defined as:

$$E_{t-1}(f_t) = E_{t-1}(p_t)z_t - w_t s_t - r_t k_t \quad (1)$$

where $E_{t-1}(f_t)$ and $E_{t-1}(p_t)$ are the mathematical expectations of profit and product prices conditional on information available in $t-1$ (prior to harvest), f_t is profit, p_t is a vector of output prices, w_t is a vector of land rental prices, r_t is the price of capital, z_t is a decision vector representing output levels, s_t is a decision vector of land input levels, and k_t is a scalar decision variable for capital input level.

Relation (1) is maximized subject to:

$$Iz_t - g_t k_t \leq 0 \quad (2)$$

$$Iz_t - B_t s_t = 0 \quad (3)$$

$$k_t \leq b_t \quad (4)$$

$$Is_t \leq c_t \quad (5)$$

$$z_t, k_t, s_t \geq 0 \quad (6)$$

where I is an identity matrix, g_t is a vector of technical coefficients transforming capital into output, B_t is a matrix of technical coefficients transforming land into output, b_t is a capital resource constraint, and c_t is a vector of resource constraints on land utilization. Constraint (2) limits output according to capital availability. Constraint (3) limits output according to land requirements. Constraints (4) and (5) restrict capital and land use to available amounts and constraint (6) imposes non-negativity.

Technical coefficients and the levels of resource constraints are constructed using census data on land availabilities, yields per acre, and net farm income. Capital coefficients are developed regionally using cost of production surveys performed by the Economic Research Service (now part of ESCS) (1), and budget data constructed by McArthur, Saunders, and Steanson (9). Cost of production indices are used to approximate technical coefficients for years when no actual data are available.

Initially the model was used to solve for the number of producers in each region over the period 1952 to 1976. Acreage controls were entered at actual levels and expected peanut prices were set equal to price supports.

A second solution was then obtained by generating random values for peanut price in each year. The peanut price was assumed to be uniformly distributed between a lower bound consisting of the peanut price time path generated by a version of the model which allows acreage to increase along pre-1949 trend and an upper bound consisting of the actual market price for peanuts. In this way, random values of peanut prices were kept within "reasonable" limits. Expected peanut prices were assumed to equal peanut prices from the preceding period. In addition to selection of peanut prices randomly in the new solution, acreage allotment constraints were assumed not binding. Free-market time paths were the result.

Random selection of peanut prices in the second solution introduces an additional complication. As peanut prices depart from historical levels, producer incomes are changed—the b_t value in constraint (4) for each problem is no longer valid beyond 1952. So that this could be allowed for, the capital constraint for each producer is redefined as:

$$\begin{aligned} b_t &= (1-\alpha) f_{t-1} \\ &= (1-\alpha) (p_{t-1} z_{t-1} \\ &\quad - w_{t-1} s_{t-1} \\ &\quad - r_{t-1} k_{t-1}) \end{aligned} \quad (7)$$

where α represents the marginal propensity to consume from producer income and the subscripts denote lagged values. Capital resources available in the current year are a percentage of net income from the previous year for each producer. Initially α is set at 0.25.

The use of relation (7) as a definition of capital resource availability provides a direct linkage over time from one programming problem to another. For this reason, the generation of pseudodata involves the solution of individual dynamic programming problems for each region. Twenty-five stages (years) are included in each regional dynamic programming problem, the results yielding the required solutions (q^* , s^* , k^*) for individual producers from 1952 to 1976.

After solution of the three regional dynamic programming problems for individual producers, the aggregate pseudo-output of peanuts produced in each year is obtained by multiplying individual peanut production levels by the number of producers in each region and summing to get regional totals.

Table 2 presents peanut prices, aggregate pseudo-output of peanuts, and the prices of cotton, corn, and soybeans (the alternative outputs in each problem). A comparison of the data in table 2 with that in table 1 indicates considerable variation in pseudopeanut production as peanut prices change. This is enlightening intuitively and consistent with prior expectations—variation has been induced artificially in the pseudodata set.

Three facets of the dynamic programming solution deserve special comment. First, the levels of the technical coefficients transforming capital and land input into output are revised over time based on actual change in capital and land productivity. Technological change is thus captured within the model, as are the effects of weather variations on

yields. Second, the number of producers is the same in both the controlled and the free-market solution. This assumption is, of course, unrealistic because the number of producers would be expected to change in a free market. And, third, the assumption that the prices of alternative output activities remains constant over time is questionable. Even though peanuts are only partial substitutes in consumption for other commodities, variation in peanut price might have some effect on these markets.

From the data in table 2, a linear supply function is estimated. Although peanut production is clearly a function of the linear programming parameters dated prior to and through each solution year, the inclusion of all the necessary parameters would introduce collinearity problems, even if the appropriate data were available on an aggregate level. Thus, peanut supply is written simply as a function of lagged output prices and lagged production (included to reflect the role of past prices in the dynamics of the programming solution). Omitting the price of corn and soybeans, because of little contribution to explanatory power and lack of statistical significance, leads to the simple supply function:

$$\begin{aligned} z_t &= \frac{1157}{(2349)} + \frac{776}{(169)} p_{t-1} \\ &\quad - \frac{16609}{(7283)} u_{1,t-1} \\ &\quad + \frac{0.238}{(.155)} z_{t-1} \\ R^2 &= 0.67 \end{aligned} \quad (8)$$

Table 2—Pseudo-output and price for peanuts, actual corn, cotton, and soybean prices

Year	Peanuts		Lagged price of—		
	Lagged pseudo-output	Price	Corn	Cotton	Soybeans
	<i>Million pounds</i>	<i>Cents/pound</i>	<i>Dollars/bushel</i>	<i>Cents/pound</i>	<i>Dollars/bushel</i>
1952	1,930	4.8	1.66	37.9	2.73
1953	2,152	5.0	1.52	34.6	2.72
1954	904	4.9	1.48	33.6	2.72
1955	1,302	5.2	1.43	35.1	2.46
1956	411	6.1	1.35	33.7	2.22
1957	393	9.1	1.29	33.1	2.18
1958	1,773	5.4	1.11	30.9	2.07
1959	502	5.7	1.12	34.7	2.00
1960	853	4.9	1.05	31.7	1.96
1961	501	10.3	1.00	30.2	2.13
1962	457	5.5	1.10	32.9	2.28
1963	259	8.9	1.12	31.9	2.34
1964	176	8.5	1.11	32.2	2.51
1965	219	6.3	1.17	31.1	2.62
1966	167	5.8	1.16	29.4	2.54
1967	5,197	10.6	1.24	21.8	2.75
1968	4,355	8.4	1.03	26.7	2.49
1969	1,674	5.5	1.08	23.1	2.43
1970	10,084	11.5	1.16	22.0	2.35
1971	7,140	10.8	1.33	22.9	2.85
1972	13,561	12.2	1.08	28.2	3.03
1973	7,121	11.9	1.57	27.3	4.38
1974	1,003	9.8	2.55	44.6	5.68
1975	4,551	11.7	3.03	42.9	6.64
1976	8,745	18.3	2.54	51.3	4.92

There is no way to produce simulated time paths with the model which would be comparable to historical time paths. This inability is, unfortunately, a major shortcoming of the pseudodata approach.

where z_t is now defined as scalar peanut production, p_{t-1} is lagged price of peanuts, $u_{1,t-1}$ is lagged price of cotton, the numbers in parentheses are standard errors, and the R^2 value is unadjusted.⁴

For relation (8), the elasticity ($d \ln z_t / d \ln p_{t-1}$ evaluated at the mean sample level is 2.1. This "short-run" elasticity is somewhat larger than similar elasticities estimated using actual time series for other crops. However, it compares favorably with Houck, Ryan, and Subotnik's (7) estimates of shortrun regional supply elasticities for soybeans, a crop with characteristics similar to those of peanuts. For the Atlantic States, Houck, Ryan, and Subotnik found a supply elasticity of 3.3; for the Plains States, 2.1. These two regions correspond roughly to the three peanut-producing regions considered in this study. For this reason, normative linear programming does not appear to yield results which are inconsistent with previous empirical findings.

THE DEMAND SIDE

The demand side of the model consists of 13 linear equations which represent the markets for peanuts and 3 peanut products: peanut oil, peanut meal, and edible peanuts. Each product market is linked by production functions to the peanut

market so that changes in consumer demands are transmitted directly as derived demands to the primary commodity markets for peanuts.⁵

Of the 13 equations included in the demand-side representation, 8 are behavioral relations and 5 are identities. The behavioral relations include a stock supply equation for peanuts; a price equation relating peanut price to other prices and other variables; shortrun production functions for peanut oil; and shortrun production functions for peanut meal; demand relations for peanut oil; for peanut meal; and for edible peanuts. Behavioral relations are specified on the basis of static theory, intuition, statistical significance of estimated coefficients, and explanatory power.

Appendix table 1 presents identities and three-stage least squares estimates of the behavioral relations of the demand side of the model. Definitions of variables in the model are presented in appendix table 2. The sample used for estimation covers the period 1929 through 1976, a total of 48 observations.⁶ Virtually all of the estimated coefficients were found highly significant statistically and of the expected sign.⁷

⁵ Although the product markets considered are not actually finished-product markets, they are treated essentially as such in this study because of the complexity of dealing with final products. Peanut oil is used in shortening, cooking oil, margarine, mayonnaise, and salad dressing. Edible peanuts are consumed as peanut butter, candy, and roasted peanuts.

⁶ A lengthy time series was necessary to obtain sufficient price-quantity variation.

⁷ The estimated coefficients on quantity in the demand relations for peanut oil and meal are not highly significant

THE COMPLETE SYSTEM

A combining of relation (8) with the demand side of the model gives the following reduced-form system:

$$\begin{aligned} y_t &= d_0 + D_1 y_{t-1} + D_2 x_t \\ &+ D_3 g_t + e_t \\ t &= 1, \dots, T \end{aligned} \quad (9)$$

where y_t is a vector of 14 endogenous variables consisting of z_t from relation (8) and the 13 endogenous demand-side variables; x_t is a vector of 11 exogenous variables not subject to control, consisting of p_{t-1} and $u_{1,t-1}$ from relation (8) and the exogenous variables from the demand side; g_t is a vector of 3 demand-side control variables, consisting of Government stocks, net Government purchases, and the price support level; e_t is a vector of stochastic residuals; d_0 is a vector of reduced-form intercepts; and the D_i , $i=1,2,3$, are coefficient matrices of reduced-form parameters.

System stability conditions require that D_1 possess characteristic roots with absolute values less than unity.

statistically. Because the markets for soybean oil and meal are so large, and because peanut oil and meal are close substitutes for soybean oil and meal, large changes in peanut oil or meal production would not be expected to have a large effect on own price. The estimated coefficients are retained, however, because simulations are performed outside the range of the historical data. Also, behavioral relations with price written on the left-hand side as an endogenous variable are justified theoretically, according to Heien (6), based on Samuelson's (13) indirect utility argument.

⁴ Changing the starting values for the pseudo random number generator used to produce the data had little effect on the estimated parameters of relation (8). The use of several pseudodata sets for estimation also did not generate estimated parameters significantly different from those presented in relation (8).

The demand side of the model can be used to generate simulated time paths which should approximate historical time paths, given peanut production levels.

If any of the moduli of D_1 exceed unity, the system is unstable, misspecification is implied, the assumptions of estimation are violated, total multipliers fail to exist, and the values of y_t explode as $t \rightarrow \infty$. Computation of the eigenvalues for D_1 yield the nonzero values: 0.78, $-0.25 - 0.09i$, $-0.25 + 0.09i$, 0.49, and 0.41. Hence, relation (9) composes stable system with cyclical time paths which converge over time to a steady state.

In addition to stability, it is necessary that relation (9) be a valid representation. Clearly, the traditional validation tests cannot be performed on relation (9) because the supply function is estimated using pseudodata; there is no way to produce simulated time paths with the model which would be comparable to historical time paths. This inability is, unfortunately, a major shortcoming of the pseudodata approach.

The demand side of the model can be used to generate simulated time paths which should approximate historical time paths, given peanut production levels. Thus, it can be validated separately from the supply side. Although this type of validation ignores simultaneity with the supply side, it does allow for partial validation. Following Naylor (11), both retrospective and prospective validations of the demand side are attempted.

For validation, simulated time paths are generated through use of the actual values of y_0 as a seed. All exogenous variables, including control variables, are set at actual levels. Generated values for endogenous variables are reintroduced as the values of lagged endogenous variables in later periods. The retrospec-

tive validation is carried out over the time period on which estimation is based, 1929 through 1976. A comparison of simulated with actual time paths gives mean absolute errors of less than 10 percent for most variables. Theil (17) inequality coefficients less than unity result for 8 of 13 endogenous variables. These results seem acceptable, given the variability in the data set.

Many analysts estimate econometric models over subsamples of available observation sets, reserving several observations for use in prospective validation. However, system (9) is estimated based on all available sample information, so that a prospective validation is not possible. As an alternative, the demand side of the system is re-estimated with data for 1929 through 1971 under the assumption that the same system specification is equally valid over both time periods. Prospective paths then can be generated and compared with actual time paths for 1972 through 1976. Appendix table 3 presents both for the demand side with 1971 endogenous values as a seed. The model tracks fairly well over a period of substantial variation in the data.

INDIRECT CONTROL COSTS AND PRODUCER INCOME

Indirect control costs and producer income effects attributable to Government controls can be evaluated by comparing simulated free-market time paths with historical time paths of the endogenous variables. This comparison is analogous to

evaluating a succession of alternative price-quantity equilibria, given shifts in the underlying behavioral relations.

So that this evaluation can be performed, simulated free-market time paths are generated by setting $g_t = 0$ for $t = 1, \dots, T$ in (9) and computing the alternative equilibria y_t over $t = 1, \dots, T$:

$$\hat{y}_t = d_0 + D_1 y_{t-1} + D_2 x_t \quad t=1 \quad (10)$$

$$\hat{y}_t = d_0 + D_1 \hat{y}_{t-1} + D_2 x_t \quad t=2, \dots, T.$$

The resultant deterministic time paths may be compared directly with the deterministic time paths generated with g_t set at actual values and e_t set at zero. Alternatively, the e_t values of (9) could be utilized to produce $\hat{y}_t$ $t=1, \dots, T$ and the results compared with the historical time paths of endogenous variables. The former alternative is pursued here because there is no loss in neglecting the stochastic error.

A convenient method for analyzing the deterministic $\hat{y}_t$ produced by relation (10) is to compare the distribution statistics of the simulated time paths with the distribution statistics of actual deterministic time paths of the system. Table 3 presents means and standard deviations for actual deterministic and simulated free-market deterministic time paths produced using relation (10). From the information in the table, the following generalizations can be made:

(1) peanut production and domestic disappearance more than double without controls; (2) stocks decrease more than one-half without controls; (3) peanut crushings increase almost eight times while domestic disappearance of edible peanuts changes little

Government control failed to reduce price variability in the domestic peanut industry. This result contrasts with the generally accepted convention that controls lead to greater price stability in commodity markets.

Table 3—Means and standard deviations of actual and simulated free-market time paths¹

Variable	Mean		Standard deviation	
	Actual	Simulated	Actual	Simulated
Production:				
Peanuts	2,333	5,805	832	3,775
Peanut oil	165	1,380	105.3	1,161
Peanut meal	112	884	64.6	734
Price:				
Peanuts	12.7	7.8	2.9	2.8
Peanut oil	18.8	11.2	8.6	5.4
Peanut meal	85.3	73.0	39.9	33.7
Edible peanuts	21.7	14.4	4.2	4.6
Difference between peanut and almonds prices	-12.5	-19.8	9.1	9.5
Peanut stocks	453	205	212	86
Domestic consumption:				
Peanuts	2,119	5,620	612	3,625
Peanut oil	130	1,349	77	1,151
Peanut meal	110	886	66	735
Edible peanuts	1,400	1,402	287	236
Peanuts crushed	535	4,217	311	3,516

¹ Units of measurement are in appendix B.

without controls; and (4) all mean prices decline in a system with no controls—peanut prices by 38.5 percent, peanut oil prices by 40.4 percent, peanut meal prices by 14.4 percent, and edible peanut prices by 33.6 percent, respectively.⁸

Standard deviations of all quantity

⁸ The simulated mean price for peanut oil at 11.2 cents compares with an actual mean price of soybean oil over the period at 13.0 cents. Traditionally, peanut oil has commanded a premium over soybean oil. The simulated mean price for peanut meal at \$73.00 compares with an actual mean soybean meal price of \$95.16. Traditionally, peanut meal has sold at a discount with respect to soybean meal.

variables increase without controls, except for edible peanut consumption. Conversely, the standard deviations of prices decline without controls. These findings suggest that Government control failed to reduce price variability in the domestic peanut industry. This result contrasts with the generally accepted convention that controls lead to greater price stability in commodity markets.⁹

⁹ The fact that price standard deviations are less in the free-market system may be a consequence of the on-off nature of controls throughout the thirties and forties.

A more interesting and specialized measure of the effects of control is obtained by computing the indirect costs imposed on consumers by the control program. In this study, indirect control costs are defined as the difference between actual costs of peanut products to consumers, and the simulated free-market costs to consumers of the same quantity of peanut products. The total cost of peanut products is:

$$C = \sum_i C_i = \sum_i \sum_t p_{it} q_{it} \quad (11)$$

where C_i is the cost to consumers of the i th peanut product over $t = 1, \dots, T$, where $i = 1, 2, 3$ for peanut oil, peanut meal, and edible peanuts. The scalars p_{it} and q_{it} represent price and consumption of peanut products. Indirect control costs (D) are defined as:

$$D = \sum_i \sum_t (p_{it} - \hat{p}_{it}) q_{it} \quad (12)$$

where the $\hat{p}_{it}$ are simulated price equilibria.

Table 4 presents actual and simulated costs to consumers of peanut oil, peanut meal, and edible peanuts in current and constant 1976 dollars for 1952 through 1976. Indirect control costs by product type are also given in the table. Indirect costs to consumers of peanut products totaled \$2.83 billion from 1952 to 1976 in current dollars, and \$4.58 billion in 1976 dollars. The major source of these costs was in the edible peanuts market—89 percent in current dollars and 91 percent in 1976 dollars.

Actual and simulated gross producer income also appears in table 4. Actual producer income (I) is defined as:

The peanut control program did increase net producer income, although gross producer income would have been greater in a free market.

Table 4—Indirect costs of control and producer income

Time path type	Costs to consumers				Producer income
	Peanut oil	Peanut meal	Edible peanuts	All products	
Billion dollars current					
Actual	0.66	0.27	7.50	8.43	7.57
Simulated free market	.40	.23	4.97	5.60	13.03
Difference	.26	.04	2.53	2.83	5.46
Billion dollars (1976)					
Actual	.97	.39	12.33	13.69	11.89
Simulated free market	.60	.33	8.18	9.11	19.89
Difference	.37	.06	4.15	4.58	8.00

$$I = \sum_t p_t z_t \quad (13)$$

where z_t is peanut production. Simulated free-market gross producer income is defined similarly, except that p_t and z_t are replaced by $\hat{p}_t$ and $\hat{z}_t$. Under a free market, gross producer income would have totaled \$13.03 billion in current dollars and \$19.89 billion (1976 dollars) from 1952 to 1976. Under controls, actual gross producer income was \$7.57 billion (current dollars) and \$11.89 billion (1976 dollars). Clearly, gross producer income would have been higher in a free market. This result is attributable to greatly expanded output, even though peanut prices are lower.

Although gross income to producers would have been higher from 1952 to 1976 with no Government control, it is not clear whether net

income would have been greater.¹⁰ This is an important question because the objective of control was to increase producer net income. An evaluation of this issue requires an analysis of the production and cost structure of producers—structures which are embodied in the programming models developed to estimate the supply function.

The production and cost structures of the programming models developed in this study are somewhat simplistic—returns to scale are assumed to be constant and only a limited number of production activities are considered. Yet they can be

¹⁰ An important distinction is made between income and net income in this study. The former is total revenue, output times price, while the latter is income above costs, representing returns to management.

used to compute net income to producers with and without controls. Net income with controls is determined by adding an additional activity to each regional linear program to represent capital used in peanut production. In the initial formulation, capital costs were not allocated per product. The regional dynamic programming problems are then solved with acreage allotments and price supports set at actual levels. Land and capital costs attributed to peanuts are subtracted from the value of peanut sales to obtain an estimate of actual producer net income from peanuts. This process gives an estimate of \$3.85 billion in current dollars from 1952 to 1976 for net producer income under controls.

Net income to peanut producers in a free market is determined by allowing peanut acreage to vary above allotments and by setting

peanut prices at simulated free-market levels. Solution of the regional dynamic programming problems under these conditions gives free-market producer net income of \$2.47 billion in current dollars from 1952 to 1976, an amount \$1.38 billion less than estimated net income under controls. Consequently, the peanut control program did increase net producer income, although gross producer income would have been greater in a free market.

CONCLUSIONS

The major objective of Government control programs has been to increase the net income of peanut producers, although specific target levels for income have never been specified by the Congress. The principal instruments of control have been an acreage allotment and price support program implemented annually since 1949.

Indirect costs of controls to consumers from 1952 to 1976 have been more than \$2.83 billion, based on the model. Adding this amount to the direct costs of controls from 1952 through 1976 (\$0.85 billion) gives total costs of controls as \$3.68 billion. Control programs added only \$1.38 billion to net producer income from 1952 to 1976. From a social cost/benefit point of view, the control program can be seen as unjustified—its costs exceeded the benefits. A direct payments scheme would have been more efficient.

The major finding is that the acreage allotment and price support programs are inefficient, given the objective of increasing producers' net income. Several shortcomings under-

lie this conclusion, however. First the modeling process is subjective. The assumption of profit maximization in the dynamic programming problems, decisions on the equations and variables to use, and the validation of the model are normative. Second, equations representing other simultaneous markets which should be included in the model are omitted. For example, the increase in peanut production in a free market must affect other commodity markets as other crop acreages are displaced by peanuts. These omissions may have resulted in the introduction of simultaneous equation bias in the estimates and structural misspecification. A model including all of the necessary markets endogenously would be extremely large, however.¹¹

The new peanut control program establishes an additional instrument for control—a production quota which provides a means of implementing a dual-level price support program. The addition of a new control instrument, however, does not change the program—acreage allotments, price supports, and purchase plans remain intact. The social costs of the new program, like those of the old, are likely to exceed the benefits. Only a direct payments scheme, and the setting of controls at levels which replicate free-market results, would result in a cost/benefit equilibrium.

¹¹ Additionally, export demand for peanut products would have to be considered since free-market U.S. prices of peanut products decline to world price levels in some years. This addition may not, however, significantly alter the findings of this study.

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Appendix table 1—Demand-side behavioral relations and identities

Equation	Variable	Estimate or definition ¹
(1)	q_t	$s_{t-1} - s_t + z_t - x_t$
(2)	s_t	$-32.9 + 17.5 p_t + 0.49 s_{t-1} + 0.84 r_t$ (26.0) (4.5) (.09) (.12)
(3)	p_t	$0.56 + 0.33 h_t + 0.42 p_{t-1} + 0.00049 q_t + 0.037 p_{1t} + 0.011 p_{2t}$ (.30) (.05) (.07) (.00017) (.016) (.004)
(4)	z_t	$-12.9 + 0.33 c_t$ (1.9) (.00)
(5)	p_{1t}	$-0.48 - 0.0042 q_{1t} + 0.46 v_{1t} + 0.00076 m_t - 0.069 v_{2t} + 0.51 v_{3t} + 0.32 p_{1,t-1}$ (.58) (.0054) (.11) (.00027) (.022) (.11) (.04)
(6)	q_{1t}	$z_{1t} - x_{1t}$
(7)	z_{2t}	$3.00 + 0.21 c_t$ (1.60) (.00)
(8)	p_{2t}	$1.92 - 0.017 q_{2t} + 0.0054 m_t + 1.21 v_{4t} - 0.30 v_{5t}$ (2.62) (.038) (.0022) (.13) (.08)
(9)	q_{2t}	$z_{2t} - x_{2t}$
(10)	q_{3t}	$162 - 1.30 v_{6t} + 0.050 m_t + 0.79 q_{3,t-1}$ (64) (1.37) (.021) (.09)
(11)	p_{3t}	$-0.87 + 0.0028 q_{3t} + 1.44 p_t$ (.73) (.0008) (.06)
(12)	v_{6t}	$p_{3t} - v_{7t}$
(13)	q_t	$c_t + q_{3t} + q_{4t}$

¹ Standard errors are in parentheses.

Appendix table 2—Definitions of system variables

Endogenous variables			Exogenous variables		
Variable	Definition	Unit	Variable	Definition	Unit
c_t	Peanut crushings	Million pounds	h_t	Price support for peanuts	Cents per pound
p_t	Peanut prices	Cents per pound	m_t	Per capita disposable income	Thousand dollars
p_{1t}	Price of peanut oil	do.	q_{4t}	Uses of peanuts other than for crushing and edible consumption	Million pounds
p_{2t}	Price of peanut meal	Dollars per ton	r_t	Government stocks of peanuts	do.
p_{3t}	Price of shelled peanuts	Cents per pound	u_{1t}	Price of cotton	Cents per pound
q_t	Consumption of peanuts	Million pounds	v_{1t}	Price of soybean oil	do.
q_{1t}	Consumption of peanut oil	do.	v_{2t}	Price of cottonseed oil	do.
q_{2t}	Consumption of peanut meal	Thousand tons	v_{3t}	Price of shortening	do.
q_{3t}	Consumption of edible peanuts	Million pounds	v_{4t}	Cottonseed meal price	Dollars per ton
s_t	Stocks of peanuts, end of year	do.	v_{5t}	Soybean meal price	do.
v_{6t}	Difference between shelled peanut price and the price of almonds	Cents per pounds	v_{7t}	Price of almonds	Cents per pound
z_t	Production of peanuts	Million pounds	x_t	Net exports, and Government sales/purchases of peanuts	Million pounds
z_{1t}	Production of peanut oil	do.	x_{1t}	Net exports and other uses of peanut oil	do.
z_{2t}	Production of peanut meal	Thousand tons	x_{2t}	Net exports and other uses of peanut meal	Thousand tons

Appendix table 3—Actual and predicted prospective time paths, 1972-76

Variable	1972		1973		1974		1975 ¹		1976	
	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
q_t	3,048	2,488	2,887	2,341	3,025	2,523	2,556	2,244	3,098	2,994
c_t	850	813	683	516	590	631	1,447	365	1,108	1,041
q_{3t}	1,694	1,675	1,840	1,824	1,800	1,892	1,870	1,878	1,800	1,953
s_t	392	420	429	434	553	462	1,146	815	1,060	765
p_t	14.5	14.1	16.2	15.5	17.9	17.1	19.6	18.1	20.0	19.9
p_{1t}	18.8	18.4	38.0	35.5	42.6	43.3	33.8	36.6	32.1	32.6
p_{2t}	102	119	170	131	126	123	143.6	138.1	212	172
z_{1t}	269	250	214	155	188	192	476	107	363	323
z_{2t}	180	177	143	112	123	137	300	80	233	226
p_{3t}	24.9	24.9	28.8	27.5	27.5	30.1	30.3	31.6	30.9	34.6
q_{1t}	174	145.5	149	95.4	157	157.3	378	10	214	277
q_{2t}	189	168	141	114	124	136	298	82	235	224
v_{6t}	-14.4	-14.3	-45.7	-47.0	-17.5	-14.9	-9.7	-8.4	-8.6	-4.9

¹ In 1975, the Government implemented a toll-crushing program to dispose of surplus peanuts. Its effects are not captured endogenously by the model.

Structural Stability and Recursive Residuals: Quarterly Demand for Meat.]

By Zuhair A. Hassan and S.R. Johnson*

Government and private sector decisionmakers and analysts commonly use quarterly estimates of demand for meat and other agricultural commodities in policymaking and forecasting. Models from which these estimates are developed are necessarily highly simplified as to demand theory and the institutional specifics of the industry. Accordingly, careful analysts and forecast users want to be assured of the accuracy with which these models approximate the true structure of the situation studied. They often make re-estimations based on different data periods and respecifications of the models to evaluate the approximations originally provided from the models.

More formal procedures for continual evaluation of structural stability for model specifications have recently begun to be developed. Various methods, beginning with the Chow (3) and F tests on various sample partitions and nested specifications, can now be used to assess structural change statistically (7, 4).¹ Two of these with considerable intuitive and computational appeal have been suggested by Brown, Durbin and Evans (2). These so-called CUSUM and CUSUMSQ tests

Methods have been developed recently for continual evaluation of structural stability for model specification. CUSUM and CUSUMSQ tests suggested by Brown, Durbin, and Evans employ recursively calculated residuals to permit the examination of structural stability. Easily developed plots can be used to generate the inferences which can be supported by the tests. This article reports on an application of these tests for five quarterly meat demand equations for Canada.

Keywords

*Recursive residuals
Structural change
Demand for meat
CUSUM
CUSUMSQ*

employ recursively calculated residuals to permit the examination of structural stability against quite complex alternatives. Easily developed plots can be used to generate the inferences which can be supported by the tests.

We report in this article on an application of the CUSUM and CUSUMSQ tests to five quarterly meat demand equations for Canada. The application demonstrates the feasibility of applying these tests in routine forecasting and policy contexts. Results indicate the importance of misspecification errors implicit in these simple models and the sample periods over which the approximation can be used with relative confidence.

THE RECURSIVE RESIDUALS

Consider the linear model of the form:

$$y_t = \underline{X}'_t \beta_t + u_t, \quad t = 1, \dots, T; \quad (1)$$

where y_t is the observation on the dependent variable, $\underline{X}_t$ is the column vector of observations on the k independent variables, β is a corresponding vector of coefficients (the subscript, t , implying that the β 's may not be constant over time) and u_t is an additive disturbance term. The first variable, X_{1t} , takes the value of unity for all T observations. The remaining regressors are assumed nonstochastic. Thus, lagged dependent variables and autoregressive schemes are excluded from the specification. The error terms are also assumed independently and normally distributed with mean zero and constant variance σ^2 . The hypothesis to be tested is $\beta_1 = \beta_2, \dots, \beta_T = \beta$.

The ordinary least squares (OLS) estimates based on T observations are given by:

$$\underline{\hat{b}} = (\underline{X}'\underline{X})^{-1}\underline{X}'\underline{y} \quad (2)$$

where $\underline{X}$ is a T by k matrix of observations on the regressors and $\underline{y}$ is a similarly defined T by 1 vector for the dependent variable. Now suppose that only r observations are used to estimate β . Then for $r \geq k$,

$$\underline{\hat{b}}_r = (\underline{X}'_r \underline{X}_r)^{-1} \underline{X}'_r \underline{y}_r, \quad r = k+1, \dots, T; \quad (3)$$

where $\underline{X}'_r = [\underline{X}'_1, \dots, \underline{X}'_r]$ and $\underline{y}'_r = [y_1, \dots, y_r]$. By introducing successive (for example, new sets) observations, one can obtain $T-k+1$ estimates of β denoted by $\underline{\hat{b}}_k, \underline{\hat{b}}_{k+1}, \dots, \underline{\hat{b}}_T$. The $\underline{\hat{b}}_r$'s may be obtained recursively (without repeated matrix inversion) from the expression:

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¹Italicized numbers in parentheses refer to items in References at the end of this article. Research support for this project was provided in part by a cooperative agreement with the former Economic Research Service, U.S. Department of Agriculture.

$$\hat{b}_r = \hat{b}_{r-1} + (X_r' X_r)^{-1} X_r' (y_r - X_r' \hat{b}_{r-1}) \quad (4)$$

where

$$(X_r' X_r)^{-1} = (X_{r-1}' X_{r-1})^{-1} - \frac{(X_{r-1}' X_{r-1})' X_{r-1} X_{r-1}' (X_{r-1}' X_{r-1})^{-1}}{1 + X_r' (X_{r-1}' X_{r-1})^{-1} X_r}$$

(See (6) and (1).)

Now consider the $T-k$ quantities defined as:

$$w_r = \frac{y_r - X_r' \hat{b}_{r-1}}{[1 + X_r' (X_{r-1}' X_{r-1})^{-1} X_r]^{1/2}}, \quad r = k+1, \dots, T. \quad (5)$$

These recursive residuals can be obtained if $\hat{b}$ is computed recursively by equation (4). Note that the w_r is the standardized prediction error of y_r when predicted from $X_1', \dots, X_{r-1}'$. The recursive residuals can be shown to be independent, given the aforementioned error assumptions. They are normally distributed with mean zero and constant variance σ^2 (2).

If the coefficient β_t is constant up to time $t = t_0$ and different from then on, the recursive residuals, w_r , will have zero mean up to t_0 and nonzero means thereafter. These residuals therefore give information about the temporal stability of the estimated coefficients. Brown, Durbin, and Evans suggested two tests based on the recursive residuals: the plot of the cumulative sum of recursive residuals (CUSUM) and the plot of the cumulative sum of squares recursive residuals (CUSUMSQ).

The CUSUM Test

The CUSUM test is based on plotting the following variable W_r against time:

$$W_r = \frac{1}{\hat{\sigma}} \sum_{j=1}^r w_j \quad r = k+1, \dots, T, \quad (6)$$

where $\hat{\sigma}$ is the estimated standard deviation based on all T observations. The expectation of W_r is $E(W_r)$ equal to 0. The plot of W_r should be distributed about this mean value, if we assume that the β 's are constant. An intuitive basis for a test for the departure of the sample path of W_r from its mean value of zero would then be to find a pair of lines lying symmetrically above and below the line W_r equals 0, so that the probability of crossing one or both lines is α , the required significance level.²

When W_r departs sufficiently from the mean under the null hypothesis, it would cross one of these lines, which would indicate the presence of a structural change. Pairs of lines satisfying the intuitive basis criteria are those through the points defined by $[k \pm a(T-k)^{1/2}]$, $[T \pm 3a(T-k)^{1/2}]$ where " a " is a parameter, whose value depends on the level of significance α . At the 5-percent level of significance, a equals 0.943 (2, p. 154). We may reject the hypothesis of constancy for the coefficients β_t at the selected significance level,

² The variances used are calculated from the ordinary least squares residuals. Alternative BLUS residuals could be employed (8). The BLUS residuals have the same distribution as the structural disturbance under the null hypothesis but are more difficult to compute.

if the sample path of W_r falls outside the pair of reference lines.

The CUSUMSQ Test

The CUSUMSQ test is based on the plot of the values for:

$$S_r = \frac{\sum_{j=k+1}^r w_j^2}{\sum_{j=k+1}^T w_j^2} \quad r = k+1, \dots, T. \quad (7)$$

Note that the quantity S_r lies between zero and one ($S_r = 0$ if $r < k+1$ and $S_r = 1$ if $r = T$), and the expectation of S_r is $E(S_r) = (r-k)/(T-k)$. Significance tests again can be performed by drawing a pair of lines parallel to the mean value line. The reference lines take the form $(r-k)/(T-k) \pm C$. The required values for C , corresponding to specific values for α (the significance level), appear in (2, p. 4, table 1). For a given value of α , we find the value for C by entering the table at $n = 1/2(T-k) - 1$ and $1/2\alpha$.

MODELS

We fit five demand equations which link per capita disappearance of beef, pork, veal, chicken, and turkey to prices and consumer income (table 1). Per capita disappearance of each commodity is expressed as a linear function of the own price, price(s) of selected other commodities (meats), and per capita disposable income. Thus, the five demand equations typify those used to study consumption behavior in applied contexts at

Table 1—Demand equations for meat and poultry, ordinary least squares,
first quarter 1965—fourth quarter 1976

Commodity	Explanatory variables ¹						
	Constant	SUD2	SUD3	SUD4	RPBF	RPRK	RPVL
Beef	19.93 (0.6786)	-0.4077 (0.2813)	-0.5200 (0.2869)	-0.1477 (0.3151)	-0.0889 (0.0246)	0.0086 (0.0091)	0.0464 (0.0222)
Pork	16.07 (0.7170)	-0.1028 (0.2968)	-0.9172 (0.2993)	-1.6179 (0.3085)	0.0373 (0.0095)	-0.0939 (0.0095)	(0.0075)
Veal	2.61 (0.1492)	-0.1709 (0.0687)	-0.1710 (0.0680)	-0.2921 (0.0697)	0.0218 (0.0050)		-0.0402 (0.0042)
Chicken	5.35 (0.2917)	-0.4552 (0.1634)	-0.1970 (0.1617)	0.8288 (0.1719)			
Turkey	5.01 (0.1251)	-3.4800 (0.0731)	-3.1400 (0.0727)	-2.730 (0.079)			
	RPCK	RPTK	RPHB	PCDY	von Neumann Ratio	F-test for hetero- skedasticity	R ²
Beef				0.0083 (0.0014)	2.44	0.48	0.92
Pork				0.0091 (0.0012)	² 0.73	³ 2.19	0.82
Veal				0.0010 (0.0001)	² 0.97	³ 2.12	0.87
Chicken	-0.0437 (0.0053)		0.0260 (0.0032)	0.0058 (0.0006)	1.89	1.45	0.90
Turkey	0.0050 (0.0033)	-0.0065 (0.0036)		0.0001 (0.0003)	1.99	1.08	0.99

¹ Equation specifications are indicated by the table. SUD_{*i*} (*i* = 2, 3, 4) are seasonal dummies for the second, third, and fourth quarters, respectively; the retail price indices per pound are, beef (RPBF), pork (RPPL), veal (RPVL), chicken (RPCK), turkey (RPTK), and hamburger (RPHB); finally, PCDY is per capita personal disposable income in current dollars. Standard errors are in parentheses. ² The von Neumann statistic indicates positive serial correlation at the 5-percent significance level.

³ The F-test for heteroskedasticity is significant at the 5-percent significance level.

disaggregated commodity levels. Their relationship to demand theory is limited and they have likely evolved through a trial and error process with the available sample data.

THE DATA

To estimate the parameters, we used quarterly observations for Canada on per capita meat and poultry disappearance, consumer price indexes (1971 = 100), and per capita personal disposable income for the period, first quarter 1965 to fourth quarter 1976. The data sources were: *Prices and Price Indexes*, Statistics Canada (Catalogue No. 62-002), *National Income and Expenditure Accounts*, Statistics Canada (Catalogue No. 13-201), and files of the Livestock Division, Statistics Canada. Newly available quarterly Canadian data were used. There was a question as to whether the specifications evolved in the annual Canadian data would prove appropriate and stable in the quarterly time frame.

RESULTS

Estimates of the five demand equations for the full sample period are presented in table 1, and plots of the forward and backward CUSUM and CUSUMSQ tests are shown in figures 1-5.³ The backward tests are conducted using the same procedure as the forward test described in the section on recursive residuals. The difference is that the observation index is reversed, the first being the last, and so on. In this case the base

observations used to begin the test procedure are from the most recent k periods. The confidence lines shown in the figures are for α level 0.05.

The estimated relationships in table 1 conform generally with results of previous applied work. All the estimated coefficients have the anticipated signs. Most of the estimates are more than twice the corresponding standard errors. The pork and veal equations show some evidence of positive autocorrelation and of increasing variance over time at the 5-percent significance level.⁴

Figure 1 (A-D) shows the CUSUM and CUSUMSQ plots for beef. Observe that the forward CUSUM plot gives the appearance of structural stability. The forward CUSUMSQ statistic deviates from the mean value line, and tends to underpredict in the early part of the

sample (up to observation 24) and then overpredict. The backward CUSUM plot also shows a tendency for overprediction (fig. 1 (C)), and the backward CUSUMSQ plot indicates a structural change at observation 29 (or 20 forward).

A corresponding series of F and Chow tests suggest that the demand equation for beef underwent structural change around observation 20.⁵ The subsample regressions in table 2 show the variation in the estimated coefficients between the two periods. The estimated coefficients for the full sample period are more similar to those in the second subsample (observation 22-48), except for the dummy variables. Coefficients of determination did not differ markedly from that for the combined sample.

The forward and backward CUSUM plots for pork (fig. 2 (A-D))

⁴ This means that the hypothesis of serial independence of the structural disturbance terms may be violated, which makes the interpretation of the recursive residuals tests somewhat difficult. Johnson and Bradshaw have shown that the CUSUM and CUSUMSQ tests are not robust in this situation (5).

⁵ The process for making Chow and F tests is familiar and so it will not be discussed. The Chow tests applied were based on the one additional new observation. The F statistics were calculated (where possible) by partitioning the sample at the point at which the recursive residual was being calculated.

Table 2—Estimated demand equations for beef during two sample subperiods

Variable ¹	Observations (1-21) ²	Observations (22-48) ²
Constant	23.76 (9.97)	19.5400 (19.99)
SUD2	-1.33 (3.15)	0.2545 (0.67)
SUD3	-1.2400 (3.45)	0.0271 (0.07)
SUD4	-0.4500 (0.50)	0.1873 (0.46)
RPBF	-0.2223 (3.85)	-0.0767 (2.86)
RPPK	0.0284 (1.70)	0.0043 (0.38)
RPVL	0.1234 (1.63)	0.0356 (1.40)
PCDY	0.0078 (0.68)	0.0089 (5.11)

¹ See table 1 for definitions of variables. ² "t" statistics are in parentheses.

³ These figures appear at the end of this article, just before the References.

deviate from the mean value lines, although these and the CUSUMSQ statistics lie within the confidence bounds. The backward CUSUM tends to overpredict up to observation 28 and then underpredict. The forward and backward CUSUMSQ plots have the tendency of being below the mean value lines. We expected this for forward CUSUMSQ (when heteroskedasticity is present) but not for the backward plot (7). Computed sequential F tests confirmed the instability of the structure in the early part of the sample period. The Chow test for backward recursion indicated a structural change at observation 29 (or 20 forward).

The veal equation in table 1 showed both autocorrelation and heteroskedasticity. The CUSUM and CUSUMSQ plots for veal appear in figure 3 (A-D). The forward CUSUM statistic begins to deviate (overpredict) from the mean value around observation 29. The backward CUSUM also diverges from the mean value as early as the second observation. These deviations in the forward and backward plots, however, are not significant at the 5-percent level. Both the forward and backward CUSUMSQ plots tend to be below the mean values but, again, not at statistically significant levels. The F and Chow tests computed at each iteration indicate structural instability at observation 29. Users should interpret these conclusions with caution because of the autocorrelation and heteroskedasticity present.

The forward and backward CUSUMSQ plots (fig. 4 (B and D)) for chicken appear more structurally stable than the forward and backward CUSUM plots (fig. 4 (A and C)).

The CUSUM plots tend to diverge from the mean value. After observation 27, the forward CUSUM underpredicts while the backward CUSUM overpredicts. None of these plots, however, crosses the confidence bounds. The series of F and Chow tests are not consistent in indicating a change in structure.

Finally, the forward and backward CUSUM plots for turkey (fig. 5 (A and C)) show strong tendencies to underpredict early in the sample period and continue to do so throughout. The deviations from the mean values, however, are not significant. The forward and backward CUSUMSQ plots (fig. 5 (B and D)) give the appearance of structural stability, as confirmed by the sequence of F and Chow tests.

CONCLUSIONS

The CUSUM and CUSUMSQ tests suggest some structural stability in the quarterly meat demand functions. Applied as a part of routine estimation procedures, these recursive residual analyses can be used to select appropriate sample periods and model specifications. The major limitation is that the power of these tests is erratic and may be low against alternative hypotheses (4). In addition, these tests are sensitive to possible errors in the specification for the distribution of the disturbances; specifically, serial correlation and heteroskedasticity.

From a practical viewpoint, these tests simply add structure to a procedure widely used in applied work for examining the appropriateness of estimated equations; that of comparing calculated residuals. The differ-

ence is that, by using the CUSUM and CUSUMSQ methods, statistical evaluations of these differences can be obtained. Along with the plots, these evaluations indicate sample periods over which the structure can be taken as stable. The recursive estimation procedure makes the tests possible with only minor additional computational burden. Major sources of predictive errors for simple models of the type presented are associated with changes in structure. Thus, the tests provide a valuable addition to the stock of diagnostic techniques available to the careful analyst.

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Figure 1A: Beef, CUSUM of Recursive Residuals, Forward Recursion

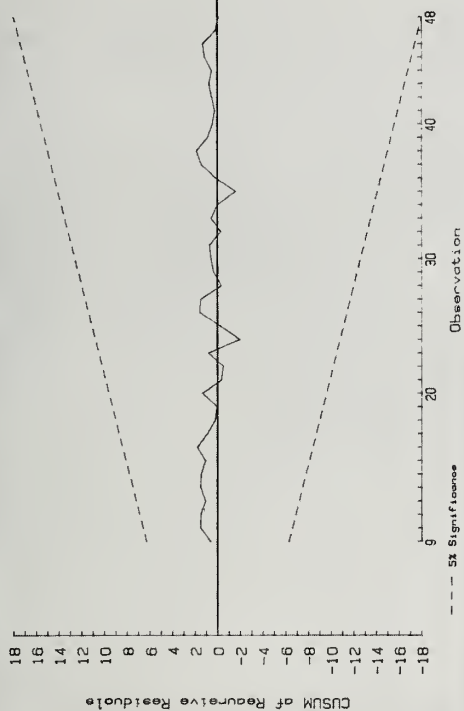


Figure 1B: Beef, CUSUMSQ of Recursive Residuals, Forward Recursion

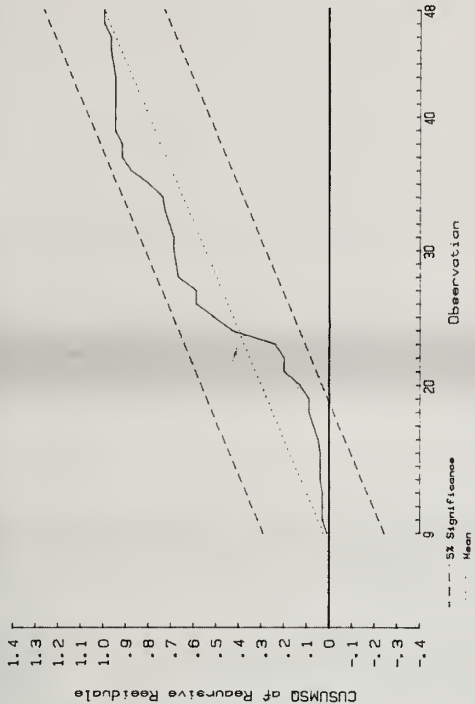


Figure 1C: Beef, CUSUM of Recursive Residuals, Backward Recursion

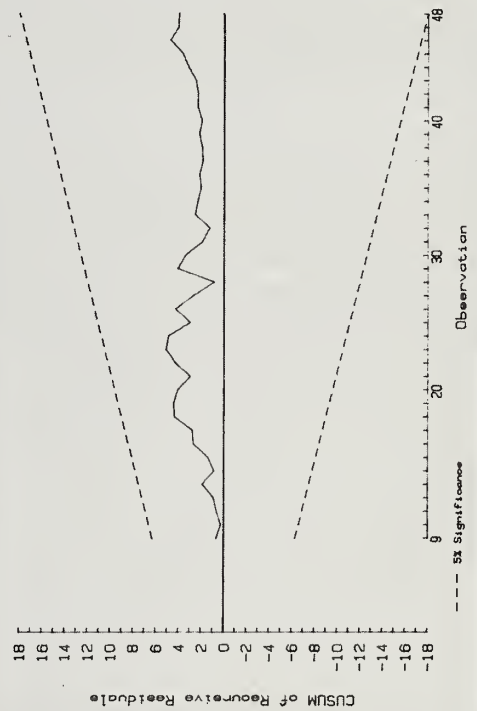


Figure 1D: Beef, CUSUMSQ of Recursive Residuals, Backward Recursion

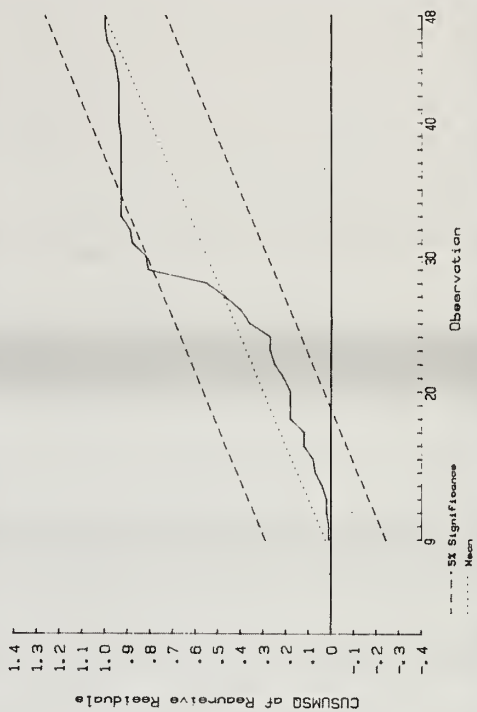


Figure 2A: Pork, CUSUM of Recursive Residuals, Forward Recursion



Figure 2B: Pork, CUSUMSQ of Recursive Residuals, Forward Recursion

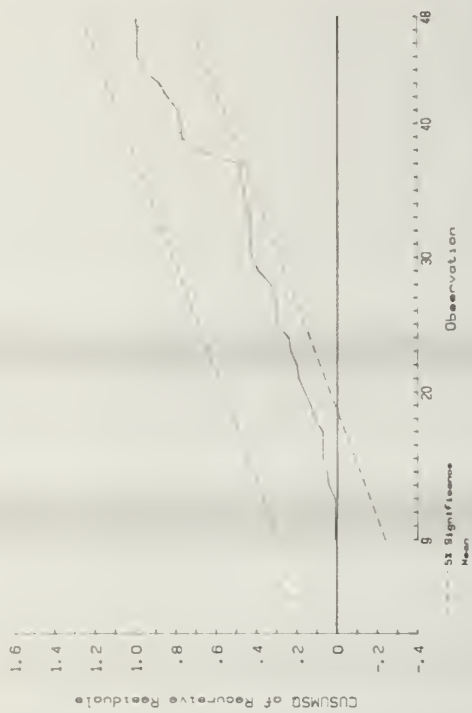


Figure 2C: Pork, CUSUM of Recursive Residuals, Backward Recursion



Figure 2D: Pork, CUSUMSQ of Recursive Residuals, Backward Recursion

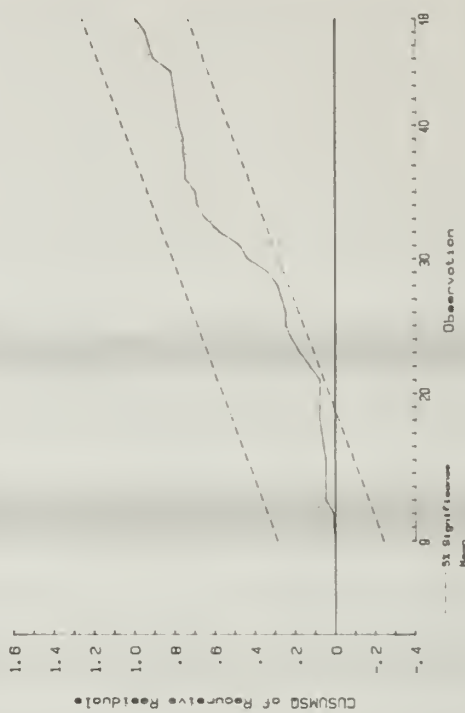


Figure 3A: Veal, CUSUM of Recursive Residuals, Forward Recursion

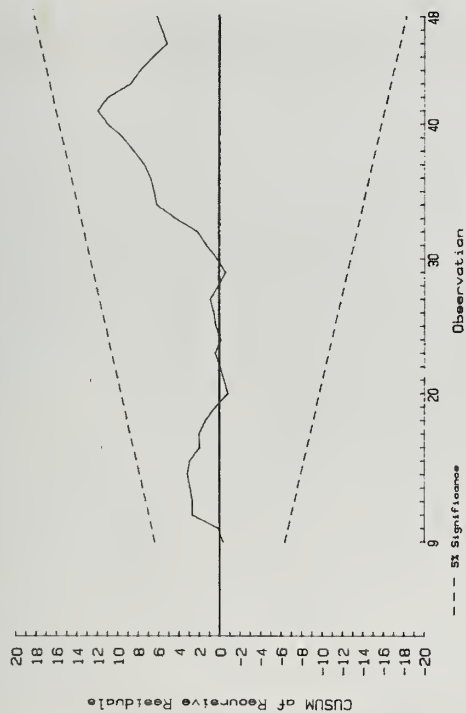


Figure 3B: Veal, CUSUMSQ of Recursive Residuals, Forward Recursion

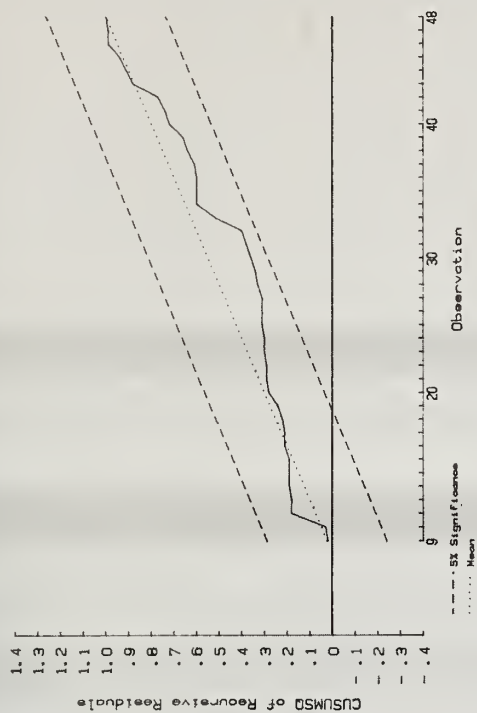


Figure 3C: Veal, CUSUM of Recursive Residuals, Backward Recursion

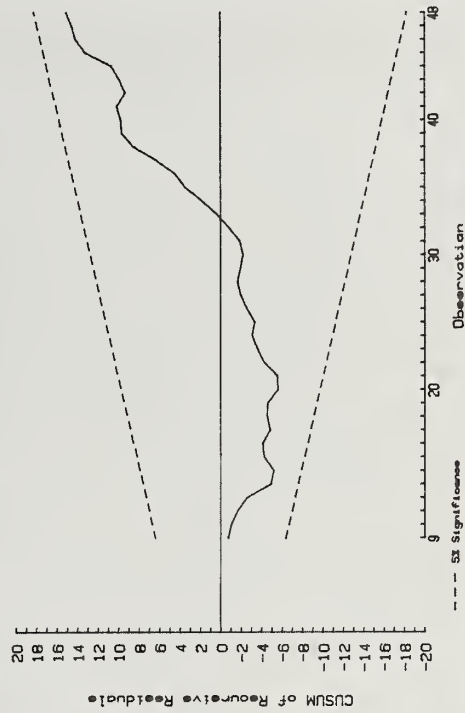


Figure 3D: Veal, CUSUMSQ of Recursive Residuals, Backward Recursion

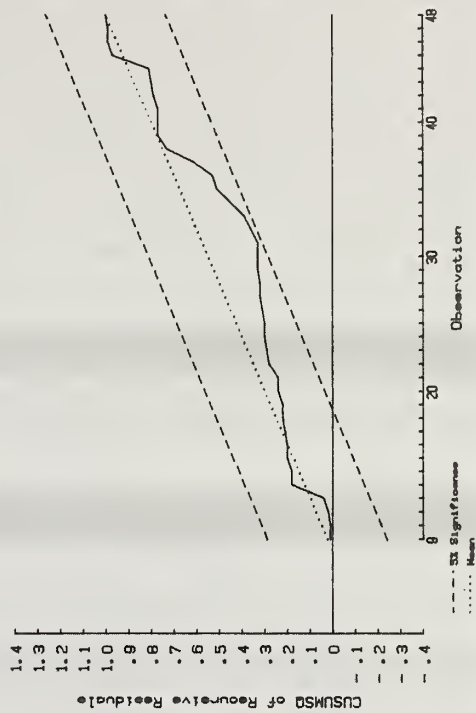


Figure 4A: Chicken, CUSUM of Recursive Residuals, Forward Recursion

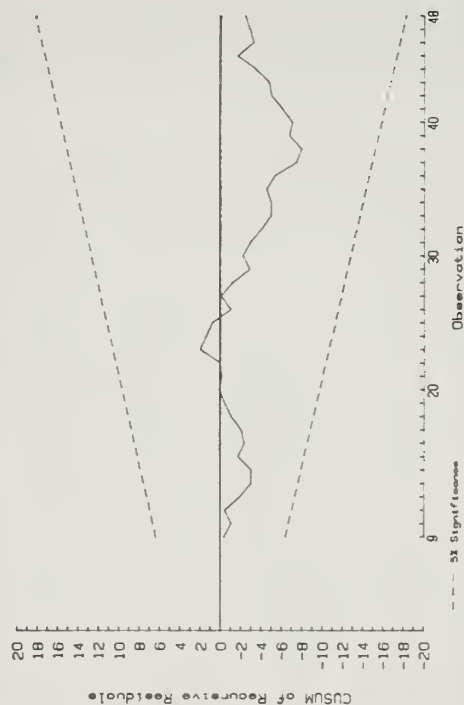


Figure 4B: Chicken, CUSUM of Recursive Residuals, Forward Recursion

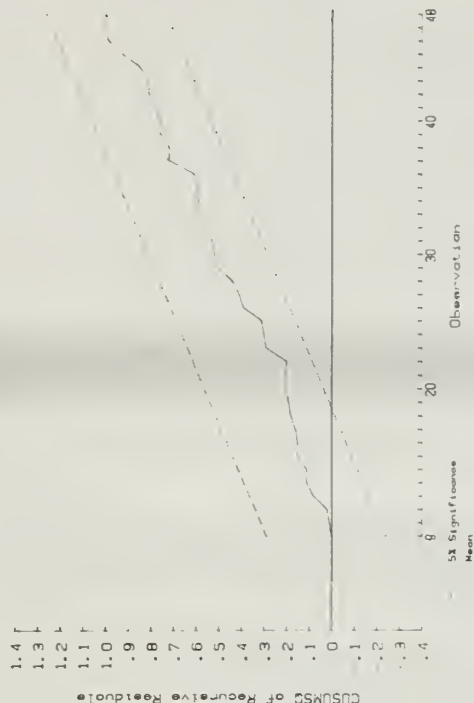


Figure 4C: Chicken, CUSUM of Recursive Residuals, Backward Recursion

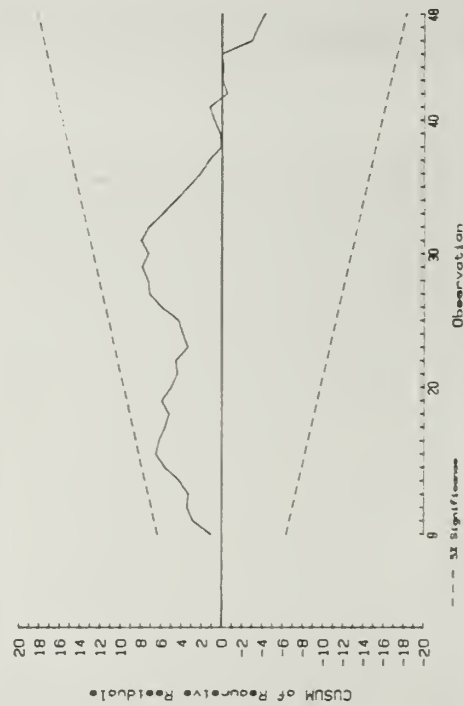


Figure 4D: Chicken, CUSUM of Recursive Residuals, Backward Recursion

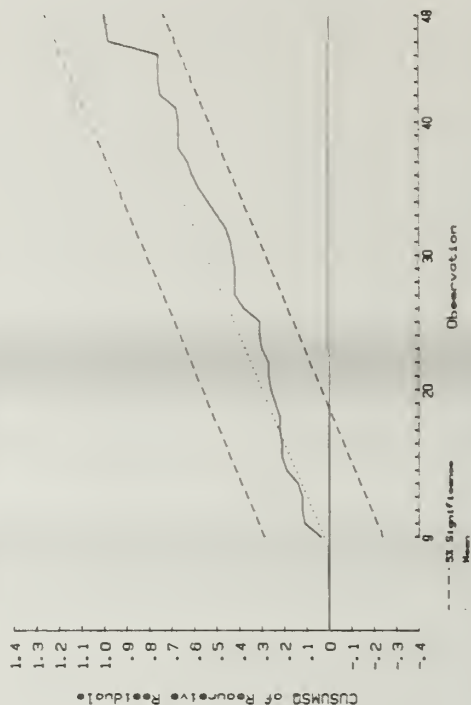


Figure 5A: Turkey, CUSUM of Recursive Residuals, Forward Recursion

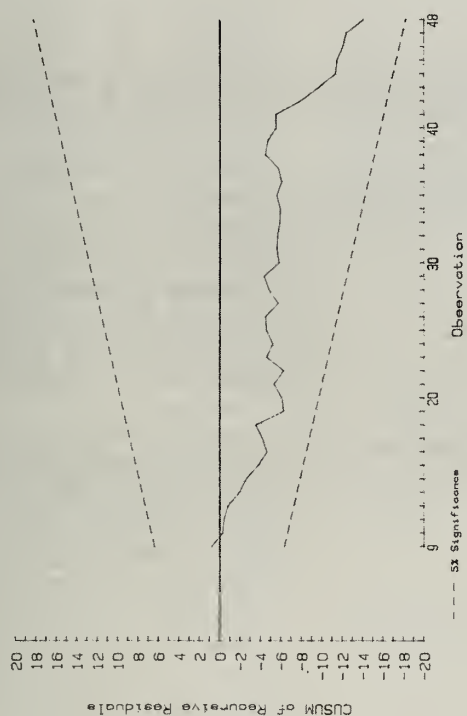


Figure 5B: Turkey, CUSUMSQ of Recursive Residuals, Forward Recursion

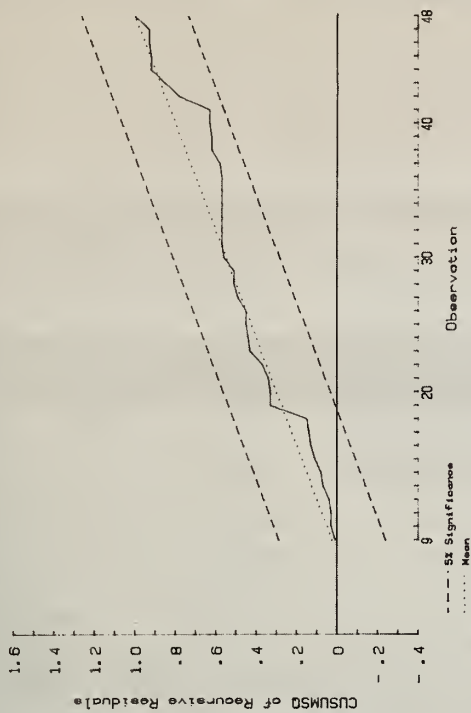


Figure 5C: Turkey, CUSUM of Recursive Residuals, Backward Recursion

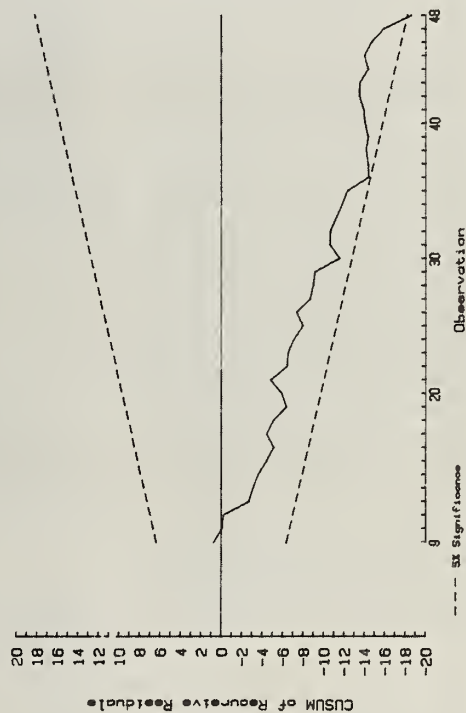
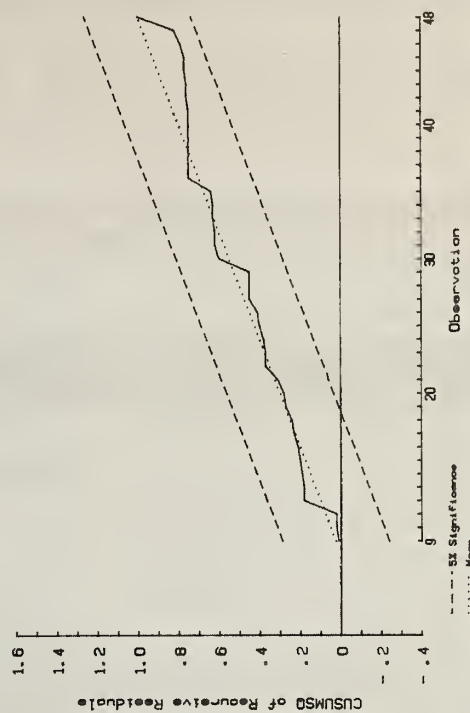


Figure 5D: Turkey, CUSUMSQ of Recursive Residuals, Backward Recursion



Estimating Demand Relations Using Futures Prices.

By William G. Tomek*

In 1974, Roger Gray (3) wrote: "The demand curve for grains may have grown steeper at higher price levels."¹ He did not test this hypothesis, but presented an example that used observations on futures prices and on crop size forecasts to compute elasticities for 2 different years. An objective of this article is to elaborate on the use of futures prices to estimate expected demand relations. Gray's simple procedure is formalised and illustrated with data for corn. Then, his hypothesis is revisited, and the results are given a somewhat different interpretation. The principal conclusion, however, is that the procedure probably has more use as a descriptive tool for students of commodity markets than as a method of estimating structural coefficients.

METHODOLOGY

The U.S. Department of Agriculture's preharvest forecasts of crop size provide a measure of expected supply. A corn production forecast, for example, is available no later than July 12 based on July 1 conditions (13).² This estimate and a corresponding futures price (say, the closing quotation for December delivery on July 13) may be viewed as the point of equilibrium of supply and

Preharvest production forecasts can be combined with contemporaneous price quotations for futures contracts to estimate demand equations, but the methodology has limitations for estimating structural coefficients. An application using data for corn highlights the difficulties. The methodology, however, does seem to be a promising descriptive tool, and it may also provide helpful information about structural relationships.

Keywords

*Futures prices
Demand
Corn
Forecasting*

demand schedules, given the information available in mid-July. Crop forecasts for corn are also made in August, September, October, and November. Hence, five observations are generally available each year on price and quantity.

The question is: Can these observations be used to estimate a demand relation? Although a correct model is needed, just four or five observations exist per year. One simple model is:

$$P_t = \alpha + \beta Q_t + e_t \quad (1)$$

where:

Q = crop size forecast made by USDA,

P = price quotation for a futures contract at the time of release of Q ,

$t = 1, 2, \dots, T$ ($T = 4$ or 5).

In demand analyses for many farm products, Q is assumed to be predetermined, and P is the endogenous variable adjusting to the changes in supply.

In estimation of a demand relation, however, equation (1) is likely

to be underidentified in some years, the first potential problem. If supply shifts while demand remains stable, the regression would provide an identifiable estimate of the demand parameters. Changes in demand, however, may be large relative to changes in supply, and the changes may be correlated. Revisions in crop forecasts are sometimes serially correlated (say, revised downward each month), and if demand changes are also serially correlated over the same time interval, the shifts will be correlated. Clearly, the slope coefficient of the estimated regression need not estimate the slope of the demand function.

A second potential problem is a lack of precision in estimation. The variance of a regression coefficient is related inversely to the variance of the explanatory variable. In many years, the variance of the crop forecast is small. Thus, even if the demand relation is identifiable, it may not be possible to obtain precise estimates of it.

A third problem is the possibility of Q 's being measured with error. The question here is not whether the forecast equals the final estimate; it typically will not. Rather, does the reported forecast correctly measure the market's expectations about supplies? Current price reflects the contemporaneous market view of economic conditions. Market participants, on balance, may not believe the USDA predictions, or crop conditions may have continued to deteriorate after the survey. The prediction is subject to varying interpretations by market participants. Thus, little correlation may exist between the forecast and price as observed at

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¹ Italicized numbers in parentheses refer to items in References at the end of this article.

² July estimates were not made in 1971-74, inclusive.

the time the forecast is released.³

The variable Q also may be inappropriate; the crop forecast may not be a good measure of total expected supply. Carryover and the production of other feed grains can also influence the price of corn.

A current price quotation for a futures contract also reflects current and expected demands. Thus, a fourth possible problem is the omission of some variables related to changes in demand. One can observe, for a year or a quarter, systematic changes in variables affecting demand, such as the number of animal units influencing the demand for corn. This becomes more complex on a daily, weekly, or monthly basis. Truly new information occurs randomly through time. If it were known or predictable, such information already would be reflected in price. When new information occurs in a perfect market, prices move promptly and correctly to the level warranted by the information (10, 14).

Markets are not perfect, but prices apparently adjust rapidly to new information (6, 11). Price changes on futures markets are expected to be martingales (10). Over a month, the

observable changes in production forecasts may or may not, as mentioned, provide a periodic measure of changing expectations about supply. But comparable measures of demand changes usually do not exist.

The empirical analysis here treats some, but not all, of the problems enumerated. For omitted variables, some modifications can be made in the model without influencing the degrees of freedom. Corn production could be deflated, for example, by animal units being fed, adjusted by estimates of carryover, and adjusted to include other feed grain production forecasts. Prices might be deflated. Many alternative model specifications are possible and are not the prime consideration here. Thus, only a few different price deflators are explored, particularly price indexes based on livestock futures prices.

A trend variable was also considered as a proxy for omitted variables. Trend was introduced through the first difference equation:

$$\Delta P_t = \alpha + \beta(\Delta Q_t) + u_t, \text{ where}$$

$$\Delta P_t = P_t - P_{t-1}, \text{ and so on.} \quad (2)$$

In equation (2), one degree of freedom is lost, and, following Samuelson (10), the error term may be heteroscedastic.⁴ Moreover, trend is likely to be a poor measure of demand

changes. The hypothesis alpha equals zero is likely to be accepted in most years, partly because expected demand did not change smoothly over the sample period. Nonetheless, the equation is of interest because of its relationship to the martingale model.

Equations (1) and (2) are fitted by least squares, but a simple instrumental variables estimator is also used to examine the errors-in-variables problem. As single equations are fitted to a limited number of observations, the identification issue cannot be faced directly.

APPLICATION TO CORN

Observations were obtained for USDA corn production forecasts by month for a series of years. These forecasts are released by the 12th of the month (13). A "final" estimate is released in January, and a revised final estimate is published the following January. Just the five forecasts in each year are used here.

Closing price quotations for December and March futures were obtained for the 13th of the same months for which crop forecasts are available. Corn prices adjust rather promptly to new information. In most years, the crop forecast is not entirely new information; traders' expectations are similar to the forecast (6).

In estimation of equation (1), both nominal and deflated prices of

³ As the crop surveys are made on the first of the month, price quotations also might be taken on the first of the month. In principle, the market may reflect the information contained in the announcement prior to the actual release of the announcement. Research by Gorham (2) and by Pearson and Houck (8) suggests that, at least in some years, there is an "announcement effect" for corn prices. Use of price quotations on the 13th of the month seems a safe choice to reflect the information in the release of the crop forecast.

⁴ Rutledge (9) did not find heteroscedasticity in changes in soybean prices. Futures prices are linked closely to cash prices for seasonally produced, continuous inventory commodities (12). Hence, the variance of the futures series is not likely to increase unless the variance of cash prices increases. Heteroscedasticity per-

haps is not a serious problem in the 4 or 5 months prior to the maturity of grain contracts, but this is an empirical question that requires analysis.

corn were considered, and three indexes were explored in deflating. The simplest to use, because it is published, is the Index of Prices Received by Farmers for Livestock and Livestock Products (1967 = 100), an index of cash prices. For estimation of expected demand for corn, however, it may be preferable to use an index based on livestock futures prices. Futures prices are available for live cattle, live hogs, shell eggs, and iced broilers.⁵ Two indexes of livestock futures prices have been computed: One uses quantity weights derived from the official index of prices received; the other uses weights based on grain consumption. Results from the analyses of nominal prices and of deflated prices using the grain-weighted livestock futures index are reported in this

⁵ The futures prices in the index are for the April delivery of cattle and hogs and the January delivery of eggs and broilers. For instance, one price in the July 1974 index is the closing price on July 13, 1974 of the April 1975 live cattle contract. January contracts are used for eggs and broilers because in some years these futures were not traded until 6 or 7 months in advance of delivery, and observations for April delivery are not always available in July. All prices pertain to the new crop year in any case, and, hence, represent market expectations about livestock prices for the new year. The weights for the prices are simply the percentages that feed grain disappearance for each livestock item represent of total disappearance for the four commodities. For simplicity the weights are computed from 1970-71 crop year data, and the price index is on a 1970=100 base. Cattle and hog futures started in the mid-sixties. Some markets in the early years were not actively traded—price quotations were not available in July for contracts requiring delivery in the next year, and data were not available until 1970.

article. (Index data appear in an appendix table.)

Both nominal and real prices were plotted against the production forecasts (figs. 1 and 2). The observations indicate a distinct break between 1970-72 and 1973-78,⁶ although of course the deflated prices vary less. The level and perhaps the slope of the price-quantity relationship have changed.

A simple instrumental variable (IV) estimator was, as mentioned above, used for some equations. If we assume Q is observed with error, the IV procedure involves ordering Q from the largest to smallest, grouping the observations using the median of Q (omitting the middle observation when five data points exist), and using the observations -1 and 1 as the instrumental variable for the two groups of observations on Q . In practice, this involves the computations:

$$b_{IV} = \frac{\bar{P}_2 - \bar{P}_1}{\bar{Q}_2 - \bar{Q}_1}$$

and

$$a_{IV} = \bar{P} - b_{IV}\bar{Q},$$

where subscripts denote the respective group averages (see 5, pp. 283-285).

Equations fitted by year using nominal prices appear in table 1. As

⁶ Since it is difficult to construct an index of livestock futures prices prior to 1970, the sample period was limited to 1970-78. However, if nominal prices or a cash price deflator are used, the scatter of observations in the sixties resembles those of 1970-72. The 1970-72 period apparently is representative of earlier years.

each equation has few degrees of freedom, the coefficient of determination adjusted for degrees of freedom, $\bar{r}^2$, is given. It can be negative and the negative coefficients should be interpreted as a zero correlation.

The slope coefficients of equations (1) and (2) are alternative estimates of the same parameter. For any given year, the first difference equation (2) generally provides a larger (in absolute value) estimate than equation (1); and, for both equations, the slope coefficients differ widely from year to year.

The intercept coefficient in equation (2) measures, the "trend," if any, in price from mid-July to mid-November of each year. Eight of the nine intercepts are negative, but only two have large t ratios. First difference regressions for 1965-69 (not reported) also have negative intercepts with small t values. Either futures prices decline seasonally or demand has declined more often than it has increased in the past 14 years (after changes in Q are accounted for). Both explanations are inconsistent with the hypothesis that $E(P_t - P_{t-1})$ equals zero for equation (2) with nominal futures prices. Cash prices decline seasonally from mid-July to mid-November, but such behavior should be anticipated in futures prices. Similarly, years with increases in demand should about equal those with decreases. It is, however, dangerous to overinterpret the results, especially for a short period of years. Statistically, most of the intercepts are zero.

For estimation of a demand relation, I see no compelling reason to use first differences. The model is of interest in examining the martingale

Figure 1

Corn: Relationship Between Futures Prices and Crop Forecasts

Futures price (dollars per bushel)

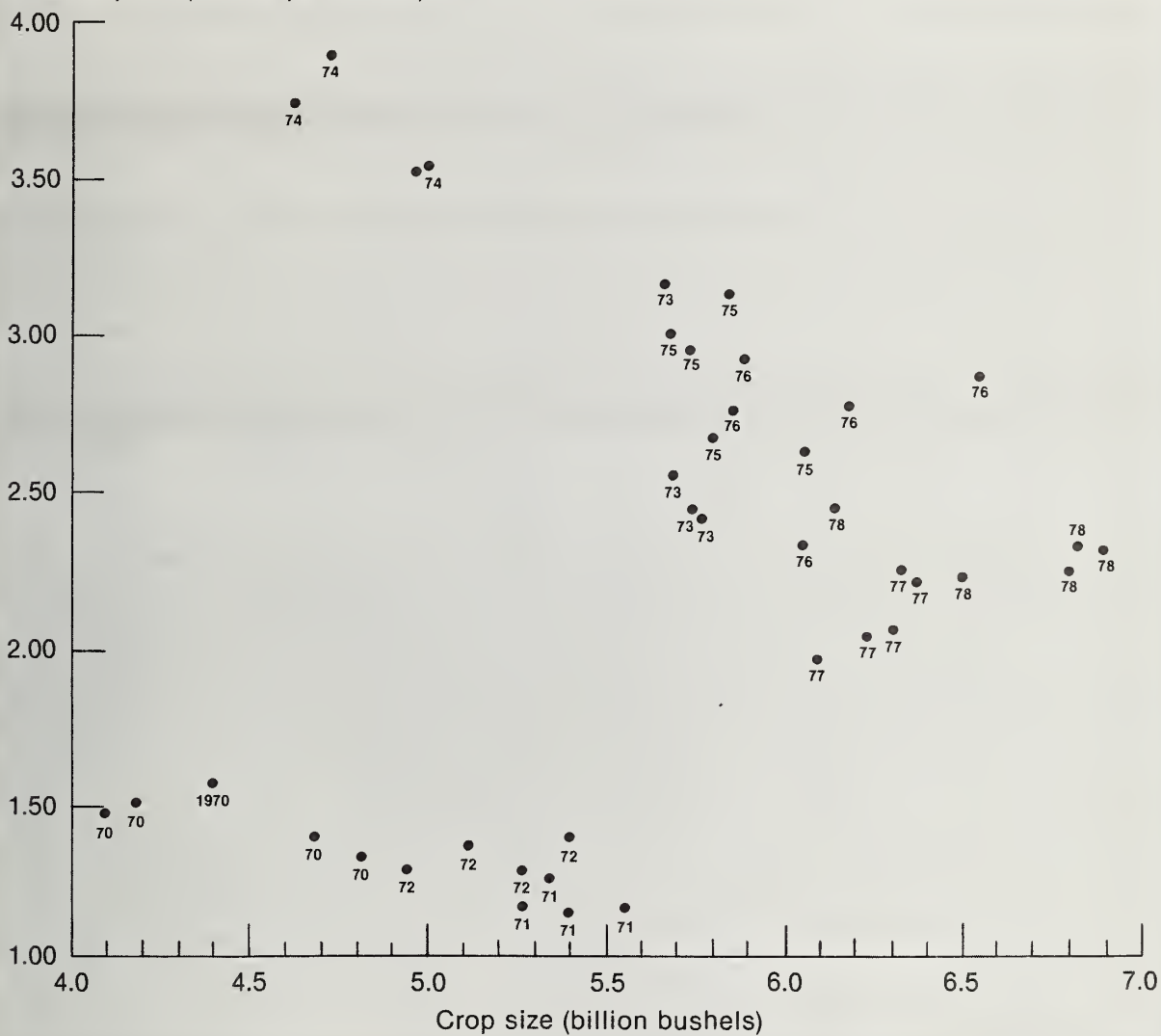


Figure 2

Corn: Relationship Between Deflated Futures Prices and Crop Forecasts

Deflated price (dollars per bushel)

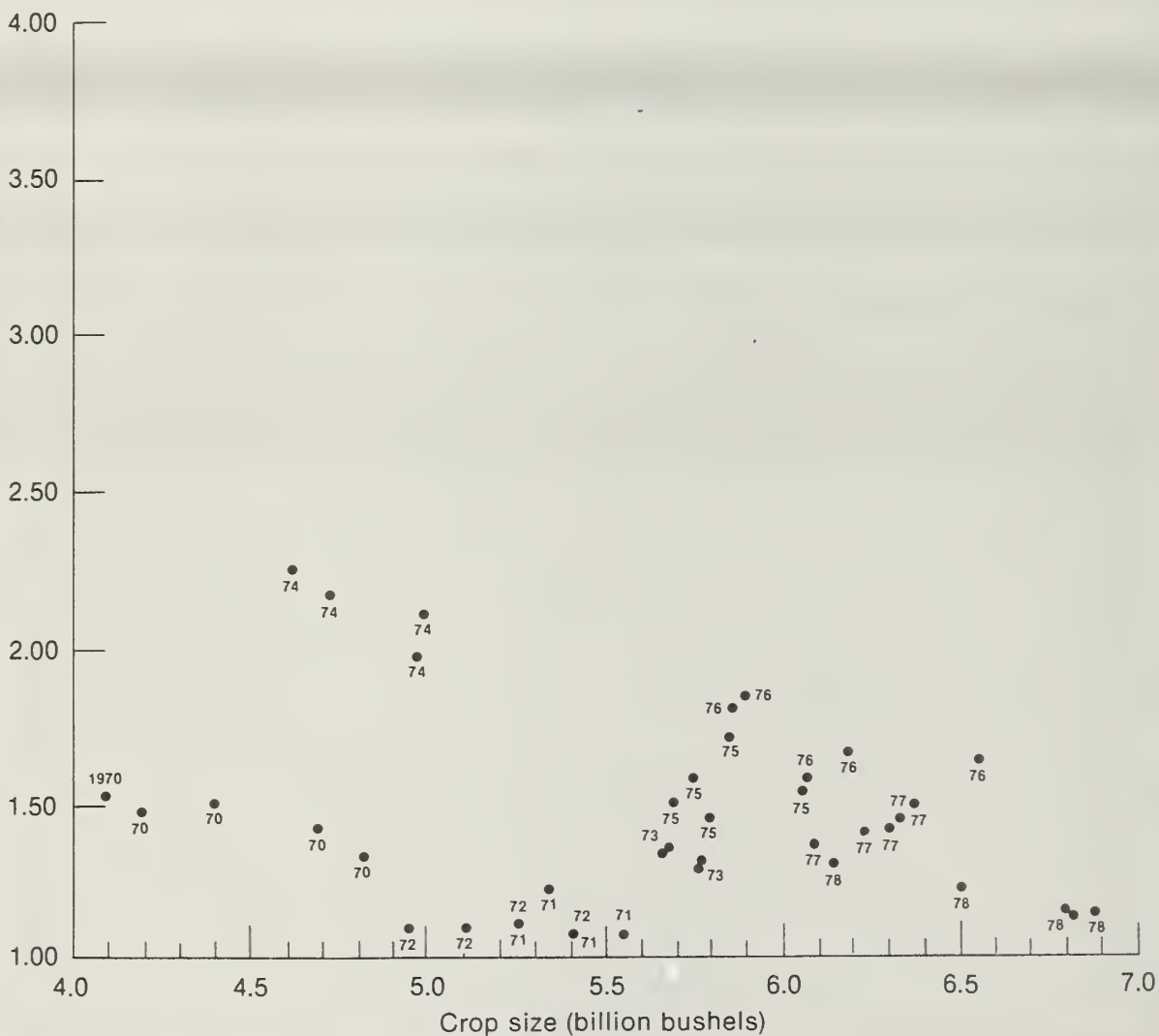


Table 1—Regression estimates by year, prices not deflated

Year	Equation ¹	Intercept	Slope	$\bar{r}^2$
1970	(1)	2.473 ² (4.59)	-0.229 (1.90)	0.39
	(2)	-0.073 (0.51)	-0.621 (0.85)	.02
1971	(1)	1.965 (1.31)	-0.147 (0.53)	-.32
	(2)	-0.059 (4.92)	0.370 (3.86)	.91
1972	(1)	0.467 (0.95)	0.167 (1.76)	.41
	(2)	-0.257 (0.97)	1.903 (1.09)	.32
1973	(1)	30.750 (1.94)	-4.917 (1.78)	.42
	(2)	-0.179 (1.39)	-4.584 (2.81)	.83
1974	(1)	7.594 (4.33)	-0.816 (2.25)	.57
	(2)	-0.073 (0.39)	-1.273 (1.15)	.36
1975	(1)	8.187 (1.97)	-0.914 (1.28)	.14
	(2)	-0.103 (0.66)	-1.782 (1.59)	.41
1976	(1)	2.114 (0.73)	0.099 (0.21)	-.31
	(2)	-0.228 (2.64)	-0.776 (2.30)	.63
1977	(1)	-3.442 (1.60)	0.884 (2.57)	.58
	(2)	-0.020 (0.42)	0.988 (3.10)	.77
1978	(1)	3.485 (4.00)	-0.179 (1.36)	.18
	(2)	0.019 (0.16)	-0.442 (0.89)	-.08

¹ Equation number in text, (2) is first difference equation. ² t ratio in parentheses.

hypothesis for futures prices, but, given the paucity of observations, the loss of a degree of freedom is serious. The estimated slope coefficients for equation (2) are even more erratic than for equation (1). Analysis of the levels of variables is simple and it seems adequate for summarizing the available information.

Equation (1) using corn prices deflated by an index of livestock futures prices (see footnote 5) was fitted both by ordinary least squares (OLS) and IV (table 2). Not surprisingly, deflating tends to raise $\bar{r}^2$. The slope coefficients are more stable from year to year after deflating, but the yearly coefficients still vary from 0.46 to -0.56 (OLS estimates). The price support program for corn influences the slope coefficients in 1971, 1972, and 1978 (and probably 1977). The loan rate places a floor under prices, and demand is essentially perfectly elastic at that price. Thus, the slope coefficient in such years is biased toward zero.

Prices in 1973 and 1974 were above support levels, and when deflated, the equations have similar slopes. The years 1975 and 1976, also with relatively high prices, have small $\bar{r}^2$'s and imprecise estimates of the slopes. The year 1970 is difficult to interpret. As the corn blight developed and production forecasts declined, prices rose, but the initial July price may have been affected by the loan rate. Hence, it is unclear whether this slope, like those of nearby years, is biased toward zero. The slopes in 1970 and 1978 are similar to each other.

Typically, the IV estimator gives results close to the OLS estimator. The IV estimator apparently has no

An equation for a particular year can be quite different from the underlying demand structure.

Table 2—Estimates of equation (1) by year, deflated prices¹

Year	Estimator ²	Intercept	Slope	$\bar{r}^2$	Range of Q
1970	IV	2.394	-0.213	0.76	706
	OLS	2.483 ³ (8.85)	-0.233 (3.69)		
1971	IV	3.800	-0.498	-.23	134
	OLS	2.399 (1.25)	-0.238 (0.67)		
1972	IV	1.090	0	-.43	452
	OLS	1.126 (9.74)	-0.007 (0.32)		
1973	IV	4.278	-0.521	.85	107
	OLS	4.420 (5.93)	-0.546 (4.18)		
1974	IV	4.838	-0.563	.69	374
	OLS	4.826 (4.90)	-0.561 (2.75)		
1975	IV	0.354	0.326	-.31	377
	OLS	1.045 (0.47)	0.087 (0.23)		
1976	IV	3.872	-0.356	.23	688
	OLS	3.309 (3.04)	-0.263 (1.48)		
1977	IV	-1.733	0.504	.74	275
	OLS	-1.464 (1.78)	0.461 (3.51)		
1978	IV	2.855	-0.253	.97	745
	OLS	2.851 (19.93)	-0.253 (11.72)		

¹Q in equation (1) is crop size forecast in billion bushels; range of Q in millions; P is December futures price for corn deflated by an index of livestock futures prices (see text). ²IV is instrumental variable defined in text. ³t ratio.

special benefit for solving the errors-in-variables problem, although this estimator is simple to compute in this particular application.

Results for equations using the price of March futures (not reported)

have slopes similar to the December equations, but typically their intercept coefficient is larger than for the December results.

Given the diversity of results, what conclusions can be drawn? To

analyze demand and especially to compare different years, one seems justified in deflating; relative prices matter. Moreover, deflation can reduce the variance of the dependent variable while leaving the variance of the independent variable unchanged. In this context, if the slope coefficient is positive or is negative with a small *t* ratio, then, of course, a demand relation has not been fitted, at least not precisely. An $\bar{r}^2$ greater than 0.6 seems a necessary, but not sufficient, condition.

A large range for Q is useful in obtaining a precise, identifiable estimate of the slope coefficient, other things being equal. But prices must be above the support level. The range of Q was large in 1978, but the variance of prices was influenced by the loan rate. If the range of Q is small, as in 1973, one must raise questions about identification. For the deflated equations, however, the slopes in 1973 and 1974 are close to each other; for nominal prices, the slopes are very different, and, presumably, the 1973 slope is far different than the true demand parameter.

In sum, an equation for a particular year can be quite different from the underlying demand structure. The best conditions for obtaining a demand relation occur when Q has a large variance and P is above the loan rate—a relatively unusual phenomenon. Considerable judgment is required in interpreting results. Nonetheless, five observations per year convey more information than the single final crop estimate and cash price. The Government support program clearly influences corn prices in certain years. Perhaps this effect would be less evident with a

single observation per year. The data highlight a possible structural change in demand, and the simple analysis of futures prices and crop forecasts is a useful descriptive tool.

In principle, the analysis could be extended by pooling the intrayear observations. A plausible model specification would allow for a change in the price-quantity slope coefficient from 1970-72 to 1973-78 and permit changes in the level of the function from year to year. Conventional demand shifters could be used. As noted, however, numerous prices were influenced by the support program. The slope coefficients for both (pooled) periods consequently are biased toward zero unless the model takes explicit account of the support program.

GRAY'S HYPOTHESIS REVISITED

In retrospect, Professor Gray was extremely fortunate to have selected 1970 and 1974 as years for comparison. Among the diverse results of the individual years, these two provide plausible approximations of demand relations for the respective periods. (Gray wrote in 1974, and, of course, he was limited to data available at that time.)

Gray based his elasticities on the arc elasticity formula which uses just two observations per year. Moreover, his computation for 1974 uses quantity forecasts made by Conrad Leslie rather than USDA.⁷ For purposes of

comparison with Gray, I use the least squares regressions for the individual years 1970 and 1974 (table 2) to compute price elasticities of demand (table 3).

Table 3—Price elasticities of demand for corn

Alternatives	Elasticity ¹
1970 equation:	
$\bar{P}, \bar{Q}$	-1.40
$Q = 4.7$	-1.27
$Q = 4.7, 1974 \text{ level}$	-2.00
1974 equation:	
$\bar{P}, \bar{Q}$	-0.78
$Q = 4.7$	-0.83
$Q = 5.7$	-0.51
$Q = 6.7$	² -0.28

¹Elasticity computed as reciprocal of the price flexibility, $F = b(Q/P)$. Estimated equation in table 2.² Based on a computed price below current Government loan rate (support level).

Gray obtained an elasticity of -0.93 in 1970 and -0.23 in 1974, and he interpreted the elasticities as being computed on two arcs of a given demand relation. It is preferable, given the differing regressions, to think in terms of two different demand schedules, but comparison of elasticities in different time periods is difficult. Measured elasticities can change because supply shifts

four observations is plausible in light of the other data. The four crop estimates also varied less than 7 percent from the final estimate, and the IV estimate differs little from the OLS estimate of the slope.

along a given demand function, which causes the elasticity to be computed at different points on the given schedule (Gray's interpretation). Elasticities can also change because of the changing slope and level of demand or for a mixture of these reasons.

The slope coefficient for the 1974 equation is twice (in absolute terms) the coefficient for the 1970 equation. Thus, a 1-billion bushel increase in corn production would have reduced the deflated price of corn 23 cents per bushel in 1970 and 56 cents in 1974. With supply constant at 4.7 billion bushels (within the range of both the 1970 and 1974 equations), the elasticity is -1.27 in 1970 and -0.83 in 1974. The level of demand, however, is larger in 1974; 4.7 billion bushels are estimated to have sold for \$1.39 per bushel in 1970 and \$2.19 in 1974 (both in real terms). With the 1970 slope at the 1974 level, the elasticity is -2.00 versus the -0.83 computed on the 1974 equation. In this sense, the elasticity in 1974 is not quite one-half the elasticity in 1970—a sharp difference, though not the fourfold difference suggested by Gray's illustration.

More sophisticated models than those used here have obtained price elasticities of demand for feed grains that range from -0.25 to -0.9 (summarized in 1, pp. 6-14; also see 7). With the 1974 equation, price elasticities vary from -0.83 to -0.28 as corn production varies from 4.7 to 6.7 billion bushels (table 3).

Gray proposed three reasons to support a hypothesis of a more price inelastic demand for corn: (a) growing affluence of consumers leading to a diet with more livestock products,

⁷In retrospect, the USDA forecasts in 1974 were reasonable, in the sense that the slope of the equation fitted to the

(b) the entry of state trading on a large scale and its influence on export demand, and (c) a tendency of some importers to stockpile during periods of shortage.

A fourth potential reason is the influence of the price support program, especially prior to 1973. The key question is whether the slope coefficient of the 1970 equation is biased toward zero by the support program. This question cannot be answered definitively. Prices in 1970 were higher than in some previous and subsequent years, yet the slope of the 1970 equation resembles coefficients in some other years where supports were effective (such as 1978).

A scatter diagram for soybeans (not shown) has the qualitative character of figure 1—a sharp break between 1972 and 1973—and soybeans were much less influenced than corn by support levels. It would, then, seem to be a mistake to attribute the possible structural change in 1973 solely to the effect (or lack of effect) of the support program. It would also clearly be a mistake to apply the slope coefficient for 1974 to years when supports are operating. The seeming structural change in demand for corn remains a puzzle that cannot be answered by the simple models used here.

CONCLUSION

In this article, I stress the difficulties of estimating a demand function from observations on futures prices for a single year. Nonetheless, in

some years, it is possible, and this methodology may permit identification of structural changes more rapidly than with annual data. An exceptionally large dose of judgment is required to use the futures price data to estimate demand relations.

The futures prices-crop forecasts observations, however, convey information even if a demand elasticity is not estimated, and they provide more information than the single final crop estimate and December price. In addition, the basic data for corn can be modified by price deflators based on livestock futures prices, by estimates of carryover, and by estimates of the production of other feed grains. Graphic analysis or simple regressions easily summarize current market conditions relative to historical conditions. Thus, the ideas presented may have more value as simple descriptive and analytical tools for extension economists and other students of commodity markets than as a procedure for fitting precise demand functions.

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Appendix: Index of futures prices for livestock

Year and month	Index 1970=100	Year and month	Index 1970=100
1970:		1975:	
July	100	July	170
August	98	August	183
September	105	September	201
October	101	October	186
November	97	November	183
1971:		1976:	
August	103	July	175
September	105	August	167
October	106	September	159
November	107	October	153
		November	148
1972:		1977:	
August	117	July	154
September	125	August	145
October	122	September	145
November	126	October	145
		November	146
1973:		1978:	
August	239	July	188
September	189	August	184
October	192	September	197
November	191	October	208
		November	204
1974:			
August	198		
September	209		
October	217		
November	225		

EXCHANGE RATES IN INTERNATIONAL COMMODITY MODELS: THE COMMON CURRENCY QUESTION.

By William H. Meyers*

In a review of problems with international commodity models, Labys (5) questions the omission of monetary factors such as inflation and exchange rates.¹ Monetary factors have been more volatile in recent years, and their effects have consequently become more important.

This note presents an evaluation of alternative methods of incorporating exchange rates in commodity models with particular emphasis on pooled cross-section time-series estimation.

Two communications in the American Journal of Agricultural Economics (AJAE) have dealt briefly with methods of incorporating exchange rates in estimated supply and demand equations for use in international commodity models. Bjarnason, McGarry, and Schmitz (1) advocated converting variables to common currency prior to estimation. Elliott (2) argued that equation coefficients should be estimated in national currency and converted to common units. Both results were derived from time-series analysis. Neither study addressed the common currency question in the context of a pooled cross-section time-series estimation model.

Pooling time-series data across two or more countries is sometimes desirable, especially in demand studies where short data series and multicollinearity in prices and income combine to limit the precision of the estimates. In this note, alternative methods of handling currency differences in time-series analysis are com-

pared and the common currency question is examined in a pooled, cross-country time-series model. Elliott thought that the estimation procedure could limit the flexibility of the model; therefore, the estimation of equation coefficients and the operational use of these coefficients are both considered here.

Currency Conversion in a Time-Series Model

Bjarnason, McGarry, and Schmitz (BMS) advocated the use of a fixed "base" exchange rate rather than the annual exchange rates for conversion purposes regardless of whether they used a price deflator. When prices are deflated, the base years of the deflator and the exchange rate should coincide. Elliott implied that the BMS method lacked the flexibility required to consider exchange rates differing from those used in estimation. He preferred to estimate the equations in national currencies and then to convert to a common currency by multiplying the price coefficients by the appropriate exchange rates.

These methods are now compared through use of a simple time-series estimation model. As the BMS method merely transforms all currency data by a constant multiple (r), it is easily shown that:

$$B = rC \quad (1)$$

where:

- B = Vector of national currency coefficients of Elliott,
- C = Vector of common currency coefficients of BMS,
- r = Scalar base exchange rate.

Thus, if B is an unbiased estimator of the true coefficients, rC is also. How-

ever, if annual exchange rates are used to convert the data (that is, if r is a vector of annual rates), it can be shown that least squares estimates of the coefficients are biased.

Constant Exchange Rate.

Let us consider a time-series demand model with K independent variables. Demand responds to internal price and income levels; therefore, all variables are assumed to be in units of national currency. Let the true model be:

$$Y = X\beta + e \quad (2)$$

where:

- Y = Vector of T observations on the dependent variable (for example, food consumption per capita),
- X = Matrix of T observations on the K independent variables (for example, prices and income per capita),
- β = Vector of K true parameters,
- e = Vector of stochastic disturbances.

The least squares estimator of β is B :

$$B = (X'X)^{-1}X'Y \quad (3)$$

Let r be the constant base exchange rate in dollars per unit of national currency,² and define the price and income variables in dollars as Z equal to rX . Thus the estimation model in dollars is:

$$Y = ZC + v \quad (4)$$

² If the variables are deflated by a price index, the Bjarnason, McGarry, Schmitz method would use the exchange rate for the year which is the base of the price index.

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¹ Italicized numbers in parentheses refer to items in References at the end of this note.

As r is scalar, the relationship between the least-squares estimators C and B is:

$$C = \frac{1}{r} (B) \quad (5)$$

It is clear from the relationship between the estimated coefficients in equation (5) that, having done the regression in dollars using a fixed exchange rate, one can always find the national currency parameters B . And it is clear that one can always convert to a different exchange rate r^* if necessary—for example for projection or simulation purposes—by calculating new coefficients C^* , so that:

$$C^* = \frac{r}{r^*} (C) = \frac{1}{r^*} (B) \quad (6)$$

These changes can be made directly in the model equations as in Elliott's method—precisely what Elliott implied was not possible with the BMS method. It demonstrates that converting with a fixed base exchange rate does not cause loss of flexibility.

Variable Exchange Rate

Bjarnason, McGarry, and Schmitz did not make explicit why it is preferable to convert with a base exchange rate rather than annual rates. Using a base exchange rate merely changes the estimated coefficients by a known constant, whereas using annual exchange rates would generally give estimates of β that are biased and not merely "less than favorable."

Considering the case of conversion with a vector of annual exchange rates (r_t) that vary across time will demonstrate this bias. Let the estimation model in dollars be redefined as:

$$Y = ZD + v \quad (7)$$

where:

$$Z = PX$$

$$\text{and } P = \begin{bmatrix} r_1 & 0 & \dots & 0 \\ 0 & r_2 & \dots & \dots \\ \dots & \dots & \dots & 0 \\ 0 & \dots & 0 & r_T \end{bmatrix}$$

The least squares estimator D is:

$$D = (X'P'PX)^{-1}X'P'Y \quad (8)$$

Substituting (2) into (8) and taking the expected value of D yields:

$$E(D) = (X'P'PX)^{-1}X'P'X\beta \quad (9)$$

The expected value of D is not equal to a constant transformation of the true coefficient vector β except in the trivial case where X is non-singular and there are zero degrees of freedom.

The conclusions are clear. For estimation purposes it makes no

difference whether one uses national currencies or transforms the data to a common currency with a fixed exchange rate. The choice of method is a question of convenience to the researcher. However, conversion with variable exchange rates gives parameter estimates that cannot be interpreted as constant multiples of the national currency coefficients.

Currency Conversion in a Pooled Model

A pooled cross-section time-series model represents an important instance in which it may be necessary to convert all values to a common currency. If there are no cross-sectional constraints on the estimated coefficients, either national currencies or fixed exchange rates can be used. This is the case when estimating the coefficients of "seemingly unrelated regression" equations. However, if a cross-sectional constraint is imposed on a price or income variable in a pooled model, it is imperative to convert that data to a common currency prior to estimation. A simple example of this case is that of using cross-country time-series data to estimate an Engel curve to test the hypothesis of equal income elasticities across countries.

Unconstrained Model

To illustrate the case of "seemingly unrelated regression" equations, let us consider two countries with estimation models of the form specified in (2) above with no cross-sectional constraints on coefficients:

$$Y_i = X_i\beta_i + u_i \quad i = 1, 2 \quad (10)$$

The unconstrained pooled model is:

In Earlier Issues

Efforts to survey the quality of housing are not new... In the unhappy event that the civilian population must be moved away from industrial areas during an emergency, rural shelter will be greatly in demand. A quick method of recording the quality of houses might be needed.

Roy Burroughs
AER, Vol. IV, No. 2
April 1952, pp. 33 and 40

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

or:

$$Y = X B + u \quad (11)$$

Let the currency in country 1 be dollars and that in country 2 be francs, and let r_2 be the constant base exchange rate for country 2 in dollars per franc. Then the pooled estimation model in dollars is:

$$Y = Z C + v \quad (12)$$

where:

$$Z = X R$$

$$R = \begin{bmatrix} I & 0 \\ 0 & r_2 I \end{bmatrix}$$

$I = K \times K$ identity matrix

As R is nonsingular, the relationship between the OLS estimators of B and C is:

$$C = R^{-1} B \quad (13)$$

The OLS estimator is consistent but not efficient for "seemingly unrelated regressions." An efficient estimator is Aitken's generalized least-squares (GLS) formula (4, p. 504), and the relationship between the Aitken GLS estimates of B and C is also:

$$C^a = R^{-1} B^a \quad (14)$$

In both the OLS and GLS results, all the coefficients in country 2 are changed by the multiple $1/r_2$ when the variables are converted into dollars. The coefficients in country 1

remain the same because the units of measurement have not been changed. These results do not differ from those for a single-country model.

Constrained Model

To illustrate the case of a constrained estimation model, let us consider an Engel curve which is estimated with data from two countries to test for the equality of income elasticities across countries.³ Estimation with nominal and real values should be compared as the results of these two cases differ.

For this purpose a simple 2-variable estimation model for an Engel curve is specified:

$$\ln Q_{it} = a_i + b_i \ln X_{it} + u_{it} \quad (15)$$

$i=1,2; t=1,2, \dots, T$

or:

$$\ln Q_{it} = c_i + d_i \ln Y_{it} + v_{it} \quad (16)$$

where:

- Q = Per capita food consumption in country i ,
- Y = Real per capita income expressed in national currency units,
- X = Nominal per capita income expressed in national currency units.

If only the income coefficients are constrained to be equal in the two countries, the intercepts may differ and the pooled estimation model can be written in matrix notation as:

$$Q = Y E + u \quad (17)$$

where:

$$Q = \begin{bmatrix} \ln Q_{11} \\ \vdots \\ \ln Q_{1T} \\ \ln Q_{21} \\ \vdots \\ \ln Q_{2T} \end{bmatrix}$$

$$Y E = \begin{bmatrix} 1 & 0 & \ln X_{11} \\ \vdots & \vdots & \vdots \\ 1 & 0 & \ln X_{1T} \\ 0 & 1 & \ln X_{21} \\ \vdots & \vdots & \vdots \\ 0 & 1 & \ln X_{2T} \end{bmatrix} \begin{bmatrix} E_1 \\ E_2 \\ E_3 \end{bmatrix}$$

$$u = \begin{bmatrix} u_{11} \\ \vdots \\ u_{1T} \\ u_{21} \\ \vdots \\ u_{2T} \end{bmatrix}$$

In the corresponding model using real income, Y_{it} replaces X_{it} in the Y matrix.

It is clear that the X (or Y) variables must have the same units of measurement in the two countries. The question is whether a fixed exchange rate or the annual exchange rates should be used to convert country 2's francs to dollars. In this case, "the same units of measurement" means that the current francs in the "nominal values" model should be converted to current dollars, and in the "real values" model, real francs should be converted to real dollars.

Conversion of current francs to current dollars requires the use of annual exchange rates:

$$r_{2t} X_{2t} = \$X_{2t} \quad (18)$$

³ The Fisher F-test determines whether or not the sum of squared residuals increases significantly when the elasticities are constrained to be equal (3).

where:

\$X\$ = Nominal per capita income in dollars,
 r = Annual exchange rate in dollars per franc,
 X = Nominal per capita income in francs.

However, equation (9) above shows that converting with the varying annual exchange rates changes the within-country variation and biases the estimated coefficients.

If a fixed base exchange rate (r_{2b}) is used to convert X , the result is:

$$r_{2b}X_{2t} = \$X_{2t} + (r_{2b} - r_{2t})X_{2t} \quad (19)$$

Thus, converting with a constant base exchange rate introduces measurement error unless the exchange rate is in fact constant. This method will generate the correct nominal value ($\$X_{2t}$) only in years when the annual exchange rate equals the base exchange rate. Therefore, for a "nominal values" model, neither conversion approach is entirely satisfactory when exchange rates are changing. If exchange rates do not vary significantly over the period of estimation, a fixed rate can be used.

For a "real values" model, the price deflator must have the same base year in both countries. Let us suppose the base year is 1975. Then the 1975 exchange rate would convert 1975 francs to 1975 dollars:

$$r_{75}Y_{2t} = \$Y_{2t}$$

where:

$\$Y$ = Per capita income in 1975 dollars,

r_{75} = 1975 exchange rate in dollars per franc,
 Y = Per capita income in 1975 francs.

In this case there is no conflict. The conversion factor preferred for the "real values" pooled model does not have undesirable effects on the country 2 estimates. The country equations can be separated after the pooled estimation, and the country 2 coefficient can be converted to a national currency coefficient if that is desired for simulations or projections.

These results can be extended to price variables and to any number of countries. The estimated coefficients from a constrained regression are not generally identical to those of the unconstrained or separate country regressions. But the Fisher F-test of equality of coefficients among regressions can be used to determine whether or not the constraint causes statistically significant changes in the coefficients.

CONCLUSIONS

When supply or demand equations are estimated for individual countries, currencies may be converted with a fixed exchange rate prior to estimation or national currencies may be used. In either case, there are no constraints on the exchange rate assumptions when the equations are subsequently used in an equilibrium model. The conversion to alternative exchange rates for simulation or forecasting can be made with price linkages or by appropriate changes in coefficients of the equations.

Supply or demand equations can be estimated with a pooled cross-section time-series model and cross-

country constraints can be imposed on any coefficients. The corresponding variables must be in common units of measurement. In a model specified in nominal values, neither a variable annual exchange rate nor a fixed exchange rate conversion is fully satisfactory. If little or no variation in exchange rates occurs during the estimation period, a fixed rate may be used. In a model specified in real values, the exchange rate for the base year of the price deflator should be used to convert variables to a common currency.

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USE OF PROBABILITY ASSESSMENTS AND SCORING RULES FOR AGRICULTURAL FORECASTS.]

By David A. Bessler and Charles V. Moore*

Analysts in Government agencies, universities, private research firms, and other institutions often make predictions about random variables that interest large groups of users. Examples include: aggregate forecasts of agricultural yield and production levels, forecasts of aggregate price and employment levels for the general economy, and forecasts of price levels for particular commodities. These predictions are often given as point forecasts—elicited with little or no explicit motivation and often with no explicit feedback or systematic evaluation.

The existing systems for reporting these forecasts implicitly recognize their uncertainties, yet these uncertainties usually are not stated precisely. Qualifiers such as “around,” “about,” or “should be around,” are often used. These rather imprecise suggestions do not summarize fully the information possessed by the commodity experts.¹

We investigate here the plausibility of forecasters' reporting, along with possible qualitative statements, their subjective degrees of belief of alternative future events. More precisely, we consider the following: first, the usefulness of the more detailed probabilistic statements, to potential users; second, methods for derivation of these probabilistic statements; and third, applications of these methods with groups of interested subjects.]

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¹The recent step taken by USDA of specifying ranges (lower and upper bounds) for some forecasts exemplifies what we consider to be a step in the right direction; however, as we argue in this note, a more general procedure can be followed.

WHY THE ENTIRE DISTRIBUTION?

In the last fifty years, economists have gone far in establishing the theoretical relationships concerning choice under uncertainty. Individual behavior, consistent with the expected utility hypothesis (6) will involve an ordering over the entire distribution of consequences.² A user of information on future events, who behaves (or would like to behave) according to these postulates of rational choice would, therefore, be interested in probability weights assigned to all possible outcomes.

Despite this theoretical motivation, some may argue that users are not properly trained to use probabilistic forecasts. That is, farmers, consumers, and Government research workers generally are trained to work with only point forecasts. This may often be true, yet training in use of probabilistic forecasts can yield great benefits—in particular, the benefits from making decisions based on a more complete description of an uncertain future. Lindley makes a similar point:

... experiments have been performed which show that individuals do not reason about uncertainty in the way described in these volumes (probabilistic reasoning) . . . To spend too much time on description is unwise when a normative approach exists, for it is like asking people's opinion of $2 + 2$, obtaining an average of 4.31, and announcing this to be the sum. It

²Italicized numbers in parentheses refer to items in References at the end of this note.

would be better to teach them arithmetic (8).

In our example here, instead of accepting a statement from a user of information that he cannot reason without one particular “best” guess, we can often instruct him in the use of probabilities.

It would also seem possible that forecasters themselves would prefer expressing their views as probabilities instead of single point estimates. As future events *are* uncertain, an

In Earlier Issues

Confusion abounds in the literature describing investigations of consumer acceptance and consumer preference. The two basic causes are the same two that cause confusion throughout the whole field of investigative research. The first is the failure to define precisely, and suitably restrict the subject of investigation. The second is the failure to employ a technique which can meet the objective.

Glenn L. Burrows
AER, Vol. IV, No. 2, p. 52
April 1952

expert should not be forced (as frequently occurs) into picking a specific figure. Doing so seemingly represents as certain that which everyone recognizes as uncertain. Some will argue that a point estimate will do enough by centering the distribution, but we believe that ignoring all possible densities can waste potentially useful information. It may not allow the expert to describe fully his knowledge about future events.

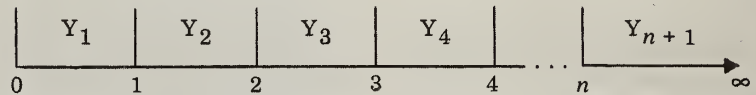
METHODS OF ELICITATION

In the past no suitable theory of elicitation existed, and any venture into this area could have been described as mere conjecture by the expert. However, in the last 10 years, a rich theory of assessment has been developed and applied in areas of similar interest—most notably weather forecasting. By use of the proper scoring rules, an expert can be encouraged to state his beliefs so that they correspond to his true beliefs (10). That is, the use of proper scoring rules implicitly recognizes the possibility that a probability assessor may not have sufficient motivation to make his stated beliefs correspond to his true beliefs. The rules provide such a motivation. In addition, the rules can be used to rank assessors, after the fact, as to the “goodness” of their assessments.³

An assessor may be faced with the task of forecasting the future value for a continuous random variable Y (Y might be a future price or yield level). The assessor can be asked to state subjective probabilities associated with $n + 1$ mutually exclusive and collectively exhaustive intervals $Y_1, Y_2, \dots, Y_{n+1}$. That is, the range of possible outcomes which Y can take can be broken up into $n + 1$ intervals (fig. 1).

We can ask each forecaster to state his best guess of the chance that the actual outcome falls into the defined categories. The intervals chosen for our example are arbitrary; yet, chosen carefully, they should represent well the uncertainty present in

FIGURE 1
Hypothetical partition of possible outcome line



the assessor's mind. Clearly, the improper choice of intervals (too many or too few) can misrepresent our assessor's beliefs. Thus, considerable care and possible experimentation will be required to use the rules we described.

Because the true beliefs exist only in the assessor's mind, there is no obvious way to determine whether the stated beliefs actually correspond to the true beliefs. To motivate the expert to make this equalization, let us present him or her with a scoring rule: $I_k(r)$. The rule rewards the assessors, depending upon the probability assessment they give (r) and the event which actually occurs (k). Of course, assessors will not know their actual scores at the time of the assessment, but they will be able to make a judgment about its expectation. That is, they will have an expected score or payoff which depends upon their true beliefs (p) and their stated beliefs (r). Their expectation will thus be given as:

$$I(r, p) = \sum_{k=1}^{n+1} P_k I_k(r),$$

where again r and p represent $n + 1$ vectors of the assessor's stated and true beliefs, respectively, while p_k represents the true belief on event k .

In choosing specific rules, we want to select one that encourages the assessors to set r equal to p . A

particular class of rules, which does just this, has been defined and studied under the label of proper scoring rules. A scoring rule is said to be strictly proper if $I(p, p)$ is greater than or equal to $I(r, p)$. That is, strictly proper scoring rules give the expert the highest expected payoff for setting stated beliefs equal to his or her true beliefs; p equals r .

Specific proper rules which have been proposed are the logarithmic rule (7), the quadratic rule (3), the spherical rule (9), and the ranked probability score (5). The logarithmic rule will be discussed here. Also see (1 and 12).

The logarithmic rule rewards or penalizes the assessor according to the stated probability associated with the event which actually occurs:

$$I_k(r) = \ln(r_k). \quad (1)$$

Because it involves only the stated probability of the event which actually occurs, this rule is rather easy to understand and can be quite useful for assessors not in the habit of stating their beliefs in probabilities. The other rules listed above define payoffs as the entire set of stated beliefs (the entire vector r). As one might expect, these more complex rules can be somewhat confusing, especially for untrained assessors. Thus, the logarithmic rule has been urged for use by untrained probability assessors (1).

³We will not treat the goodness evaluation aspect of these rules here. For discussion of this point, see Winkler and Murphy. Suffice it to say, that the same rules can be used to rank assessors afterwards as to goodness.

It is desirable, other things being equal, to pick the rule which is most responsive to deviations of the stated beliefs (r) from the true beliefs (p).

Obviously, the rule defined in equation (1) will give an assessor negative payoffs. Its range is minus infinity to zero. While this interval is theoretically acceptable, it presents a practical problem: we usually do not wish to give assessors extremely large negative payoffs (how do we give, for instance, a payoff of minus infinity?). Usually, in elicitation work, we do not wish to give negative payoffs at all. To avoid this problem, Shuford and others suggest we modify the rule given in equation (1) by truncating the payoffs at some arbitrarily selected small probability and adding a constant to all payoffs—a constant sufficient to make all payoffs positive (11). That is, we can amend equation (1) as follows:

$$I_k(r) =$$

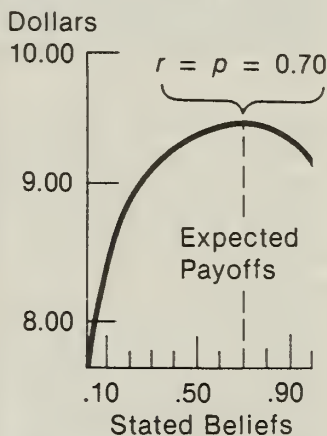
$$\begin{cases} b & , \quad 0 \leq r_k < 0.01 \\ a + \ln r_k & , \quad 0.01 \leq r_k \leq 1. \end{cases}$$

The constant b should be selected to be less than the payoff given to the stated belief of (0.01); a should be selected so all payoffs are positive.

The truncated rule is not strictly proper. As one might guess, problems exist in meeting the proper conditions at the point of truncation. However, in most practical situations (except when small probabilities are desired), the truncated rule ought to give good results.

We now graph the expected payoff from a logarithmic rule applied to the probability assessment for two mutually exclusive and exhaustive events. We apply the truncated rule with $b = 0$ and $a = \$10$. We assume for illustration that the assessor's true belief on the first event occurring is p equals 0.70. Thus, the belief on the second event occurring is $(1-p)$ equals 0.30. In figure 2, the

Figure 2
Hypothetical Expected Payoff from the Truncated Logarithmic Rule



horizontal axis represents alternative stated beliefs or assessments on the first event. The vertical axis represents the expected payoff associated with each of these stated beliefs. As one can see, the assessor will maximize the expected score by choosing stated beliefs to correspond with his or her true beliefs; so that r equals 0.70 and $(1-r)$ equals 0.30. Any other assessment will result in a lower expected score. For example, if the expert sets r equal to 0.40, the expected payoff would be \$9.21, which is less than the \$9.37 if r equals 0.70.

A scoring rule needs to be sensitive to deviations of r from p . It is desirable, other things being equal, to pick the rule which is most responsive to deviations of the stated beliefs (r) from the true beliefs (p). One can see in figure 2 that the logarithmic

rule is not highly sensitive to small deviations. Winkler and Murphy confirm this low sensitivity (15). They compare the sensitivities of three rules—logarithmic, quadratic, and spherical—and find the logarithmic rule the least sensitive. The practical researcher, then, must weigh the benefit of using the logarithmic rule against the cost of its lesser sensitivity. When lengthy training sessions are feasible for assessors, the research worker may opt for the more sensitive quadratic or spherical rules.

EMPIRICAL APPLICATIONS

Scoring rules have been used to encourage "good" assessments in various fields, with probably the greatest success in weather forecasting (13). Applications in other fields include stock market price forecasting (12) and football score forecasting (14). We have adapted the logarithmic rule for elicitation of price and yield distributions for California field crops.

In our particular studies, we found the truncated logarithmic rule to be convenient and reasonably accurate (1 and 2). We wanted many assessments (50-75 assessors) and had a relatively short period for assessor training. By forcing the assessors to respond in predetermined discrete probabilities (0.00, 0.10, 0.20, . . . , 1.0; see (4)), we could get sensible assessments from them in sessions lasting a little over an hour. We can never be absolutely sure that such assessments are accurate. Yet substantial agreement exists among assessors in similar environments and the assessments agree (in a probabilistic sense) with their time series representations (2). Thus, we feel encouraged about future use of scoring rules in probability assessment tasks.

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In Earlier Issues

It is clear that economists know what inflation is, how it arises, and what tools are necessary to prevent it, although some of the proposals suggested by economists are not easily accepted politically. Perhaps the major differences among economists relate to the importance allocated to each of these tools. It is also clear that no single tool will suffice.

Nathan M. Koffsky
AER, Vol. IV, No. 2, p. 61
April 1952

By Klaus F. Alt and John A. Miranowski*

The environment interacts with agricultural production activities in two primary ways: it contributes raw material inputs and it accepts the residues of production and consumption activities. Historically, farmers could either treat wastes at their own expense or they could let the environment absorb them. Now, a portion of the environment's absorptive capacity has been preempted by residuals from nonagricultural activities, and today's agricultural wastes are often less biodegradable. Thus, the absorptive capacity of the environment is frequently exceeded, and the demand for a cleaner environment is rising. The result has been an increasing demand for pollution abatement policies.

POLLUTION ABATEMENT OPTIONS

The policy options proposed for agriculture include: charges, subsidies, marketable rights, and direct regulation. The objective of each policy is to encourage farmers to lower their emissions of pollutants. Charges penalize emissions, which induces polluters to find disposal methods which are less costly than the penalty that they would pay for releasing untreated residuals. Subsidies act like bribes. The response to a subsidy is generally considered symmetrical to that of a tax or charge. Marketable rights allow limited residuals to be disposed of after competitively purchased permits have been acquired. Direct regulations spe-

cify what actions the polluters must take.

The merits of these policies can be examined through use of pollution abatement demand and supply functions. The demand function measures society's willingness to pay for alternative levels of pollution abatement. It quantifies society's desire for a cleaner environment. The supply function measures the added cost of supplying various levels of abatement. It should account for all the social costs of abatement, including the information, enforcement, and administration associated with the abatement policy, as well as the direct abatement costs incurred by farmers. As we have demonstrated, ignoring these costs will underestimate the added costs of abatement activities and may lead to establishing excessive levels of abatement (4).¹

CHOOSING THE OPTION

The optimal level of pollution abatement is defined as the level at which the cost of supplying the last unit equals the price that society is willing to pay for that last unit. This level can then be imposed administratively by any of the policy options mentioned; each of them could be equally efficient in the absence of real-world transaction costs, as Fisher and Peterson point out (2).

However, we know little about society's demand for a cleaner environment, or alternatively, the strength of society's willingness to pay for the implied pollution abatement. So we are operating with inadequate and imperfect knowledge

about the demand function. We have only normative estimates of the abatement supply curve. Given this quality-of-information problem, the level of pollution abatement selected will likely be in error, which implies a suboptimal abatement level and a misallocation of resources. Thus, an important aspect of policy research is to isolate pollution policy instruments that are likely to minimize the social cost of an error. We now demonstrate that knowledge of the elasticity of the abatement supply function can be used to determine which policy instrument will minimize such cost.

MINIMIZING SOCIAL COSTS OF AN ERROR

Figure 1 presents elastic (SE) and inelastic (SI) abatement supply curves and a possible demand curve (D).² Consider establishing the level of abatement (through marketable rights or direct regulation) in the absence of perfect knowledge. In the elastic supply case, the social cost of requiring abatement at level b when level a is the optimum is the area α . In the inelastic case, the social costs of level b when a is the optimum level is area $\alpha + \beta$.

Also consider a policy instrument in which we set the price, with a tax/charge or a subsidy/bribe (fig. 2). For these policy options, the social cost of an error for an elastic abatement supply curve is area α , which is greater than area β for an inelastic supply situation.

The elasticity of the abatement supply function, then, is important in selection of an appropriate policy instrument. If the abatement supply

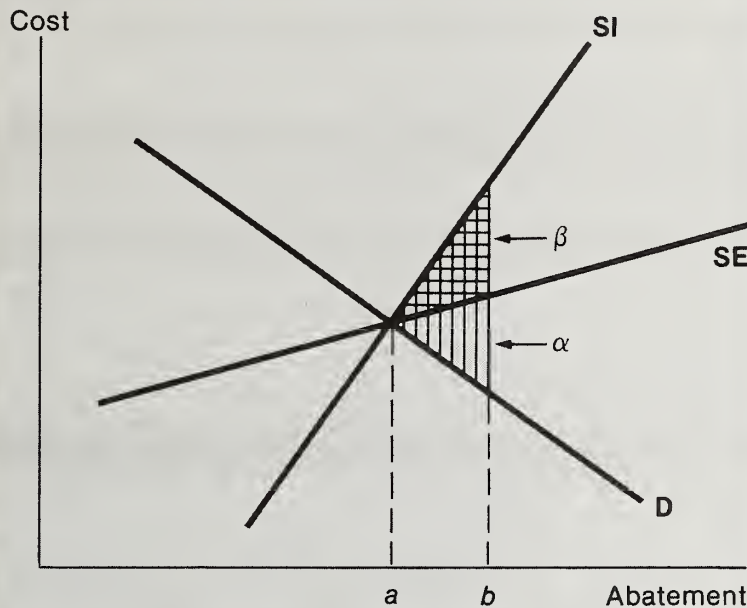
*Klaus F. Alt is an agricultural economist with the Natural Resource Economics Division, ESCS, and a USDA collaborator in the Department of Economics, Iowa State University, Ames. John A. Miranowski is an assistant professor in the Department of Economics, Iowa State University.

¹ Italicized numbers in parentheses refer to items in References at the end of this note.

² Previous work by Alt and Miranowski (1) demonstrates that the result is insensitive to the elasticity of the demand curve.

Figure 1

Cost of Error in Permit Program for Alternative Abatement Supply Functions



curve is inelastic, a price incentive scheme implies less potential social cost of an error. If the abatement supply curve is elastic, setting the level of abatement by direct regulations or by auctioning a fixed quantity of pollution rights implies less potential cost of an error.³

An abatement supply function is likely to have both elastic and inelas-

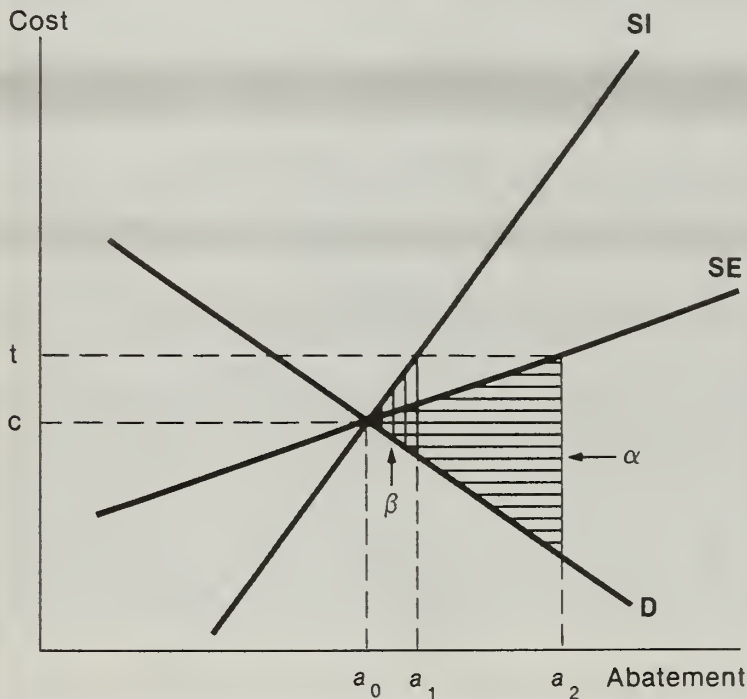
tic ranges, and the elasticity in the relevant range must be determined. Taylor and Froberg illustrate abatement supply curves for alternative policy instruments in controlling nonpoint source pollution in agriculture (5). At lower levels of control, the abatement supply curve is elastic; at higher levels, it becomes inelastic. Kneese and Schultz document similar increasing marginal costs of abatement for industrial firms (3). Thus, at less restrictive levels of pollution control, the social cost of an error tends to be minimized when the policy selected prescribes the desired

level of abatement (marketable rights or direct regulation). As abatement demand increases and abatement supply becomes inelastic, policy instruments relying on price incentives (taxes or subsidies) tend to minimize the social cost of an error.

The transaction costs of policy instruments should be included in estimates of the abatement supply function. These costs may alter the shape and the elasticity of the curve. Particularly at higher levels of abatement, the marginal enforcement costs likely will rise because of higher resistance by polluters. Increased

³ Of course, the choice may not always be as clear, particularly if the abatement supply curve is unknown and the elasticity cannot be determined.

Figure 2
Cost of Error in Tax Program for Alternative
Abatement Supply Functions



transaction costs will tend to make the supply curve more inelastic at higher levels of abatement and increase the advantages of a price-incentive scheme.

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NONTARIFF AGRICULTURAL TRADE BARRIERS

Jimmy S. Hillman. University of
Nebraska Press, Lincoln, Nebraska,
1978, xviii and 236 pages, \$13.50.

*Reviewed by William E. Kost**

Nontariff trade barriers are important, though generally overlooked, aspects of international trade in agricultural products. Hillman is concerned with the proliferation of these trade barriers. This concern hinges on the conventional free trade arguments. Nontariff trade barrier growth is viewed as an impediment to future international cooperation and to world agricultural efficiency. He maintains that unless nontariff trade barriers are reduced, world markets will become further fragmented and the development of efficient, low-cost agriculture will be severely hampered. The theme of the study is that:

Agricultural trade barrier problems residual to the Kennedy Round negotiations, buttressed by the nature of their uniqueness, are likely to become more complicated and important . . . The likelihood of international trade breakdown will increase proportionately to the unwillingness of the major agricultural producing and trading nations to reduce the adverse impact of their domestic farm policies upon international trade (p. 181).

Any obstacle to the flow of trade, except traditional customs duties, that discriminates against foreign countries is considered a nontariff trade barrier. Hillman analyzes the development of nontariff trade barriers, classifies them by type, catalogues barriers of several countries, and discusses the problems of international negotiations aimed at relaxing barriers.

His first three chapters review the

emergence of nontariff trade barriers. Prior to the thirties, tariffs were the principal tool of agricultural protection in the developed countries. During the financial and commercial breakdown in the thirties, major agricultural trading countries implemented domestic agricultural price and income policies to cope with low agricultural prices and mounting surpluses. A series of nontariff trade barriers were devised and implemented by the developed countries, as tariffs were unable to protect domestic agriculture. These barriers effectively supported domestic agriculture. Hillman concludes that "most of the effective trade restrictions on agricultural products that countries have adopted . . . have been adjuncts to their domestic farm policies . . . nations have not developed a separate and identifiable trade policy for farm products."

Trade liberalization negotiations have been conducted through the General Agreement on Tariffs and Trade (GATT) framework but these have focused primarily on tariff reductions. Not only were tariffs more tangible to negotiate, they were also less critical in terms of their domestic policy impacts. To the extent that negotiated tariff reductions create severe domestic hardship, offsetting nontariff trade barriers could be implemented. This process, over time, has brought nontariff trade barriers, relative to tariff barriers, to the forefront of current trade policy issues.

Chapter four presents a classification of various nontariff trade barriers that ranges from quotas, subsidies, and variable levies all the way to mixing regulations, import calendars, labeling requirements, and health and sanitary requirements. The major theme of this chapter is to impress upon the reader the myriad of existing trade barriers.

The next three chapters catalogue nontariff trade barriers. Chapter five focuses on the U.S. Section 22 quota system, the European Community (EC) variable levy system, and the Japanese import quota restrictions. Chapter six catalogues the various barriers existing in the United States, the United Kingdom, the EC-6 countries, and Japan. Chapter seven details the nontariff trade barriers for red meat animals and red meat in these same countries. Barriers in developing countries are not discussed.

The final chapter presents the problems involved in liberalizing nontariff trade barriers. The delicate relationship between these trade policies and domestic farm policies creates major difficulties. Countries are unwilling to negotiate domestic farm policy in an international forum. This situation, coupled with severe difficulties in measuring levels of effective economic protection by these barriers, makes Hillman somewhat pessimistic as to the effectiveness of any negotiations in reducing nontariff trade barriers.¹

I have mixed feelings about this book. The author raises an important and frequently overlooked issue in international agricultural trade. He defines the problem and traces the evolution of nontariff trade barriers. For these reasons alone, the book is useful and should be read. However, I expected more.

Hillman recommends two prerequisites for successful nontariff trade barrier negotiations: measuring levels of effective protection and determining the impact of agricultural policies (including these barriers) on agriculture. Although nontariff trade barriers are broadly catalogued, no attempt is

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¹ This book was written at the start of the Tokyo Round of GATT negotiations.

Unless nontariff trade barriers are reduced, world markets will become further fragmented and the development of efficient, low-cost agriculture will be severely hampered.

made to measure effective protection levels. Nor does he consider the problems involved in measuring effective protection levels for nontariff trade barriers. The effects of agriculture and trade policy on output, consumption, prices, and income are crucial in any negotiation. Hillman does not analyze the economic impact of nontariff trade barriers on agriculture beyond offering the general statement that they restrict trade. He does not discuss how one would incorporate nontariff trade barriers into economic analysis.

My appetite was whetted. In picking up this book I had hoped either to be able to analyze better the impacts of nontariff trade barriers or

to find out what the impacts were. Instead, I found only a repetitious statement of the problem. What is said three or four different ways in 200 pages could have been said well in 50. For a shorter statement of the problem, read chapters two through four, and eight.

In two technical areas I disagree with Hillman although neither significantly affects the overall usefulness of the study. In his discussion of the EC variable levy (pp. 81-88), he argues that the variable levy "must, of necessity, act like a quota." Like Koenig (p. 203), I disagree. The levy limits imports, but not to any specific level. It is a variable specific duty and not a quantitative barrier.

In his analysis of tariff versus quota impacts, Hillman gives examples of the imposition of quotas in the face of inelastic supply in the exporting country. However, such quotas do not cause the price to fall to the point where the exporting country's supply equals its own demand, as Hillman shows. Price will be above that level. The country must export a volume equal to the importing country's quota-constrained imports.

In summary, the book raises an important issue, one where relatively little analysis has been focused. Read it, or parts of it, for a good statement of the problem. For substantive analysis, you will have to look elsewhere.

In Earlier Issues

Ideas are powerful forces for change, but in social science they include ethical ideas of equality, democracy, and justice—not merely the ideas of a self-regulating mechanism so characteristic of natural science.

Bushrod W. Allin
AER, Vol. IV, No. 2, p. 59
April 1952

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Transit is defined as the privilege of stopping a shipment in route to enable a process or operation to be performed on the article, and of reshipping to final destination at the through rate applicable from the original shipping point to destination. The impact of this device on American industry is great.

Joseph E. Rickenbacker
AER, Vol. IV, No. 2, p. 63
April 1952

RURAL POLICY RESEARCH ALTERNATIVES

David L. Rogers and Larry R. Whiting
editors, Iowa State University Press,
Ames, Iowa, 1978, 245 pages, \$6.95.

*Reviewed by Melvin R. Janssen**

In the private economic sector, the theory of the firm has been a relatively simple type of analysis. The goal of maximizing profits limited attention to the economic sphere. Traditionally, the number of decisionmakers in each firm was small, and effects of decisions external to the firm were generally not examined. Complexities were largely confined to production-marketing relationships for multiproduct firms. Recently, environmental and social concerns have widened the arena for private decisionmakers within the economic sector, although problems are less complex than those faced by public decisionmakers.

Simple application of this theory of the firm is not adequate for dealing with emerging public problems. The realm of public services presents measurement problems, which include the level of services to be provided. The number of decisionmakers for public policy decisions is frequently larger than in the private firm, and they often conflict in their goals. A decision is likely to have economic, social, political, and psychological implications that do not conform to the theory of the firm. These problems prompted the North Central Regional Center for Rural Development to sponsor a conference on Alternative Methods for Public Policy Research in Rural America. The edited papers from the conference comprise the volume reviewed here.

In the lead paper, Daft expands the public policymaking arena to include evaluative, regulatory, and judicial activities often overlooked.

When considering why much information never gets through, he proposes the following seven standards of measurement of policy information: relevance, timeliness, credibility, clarity, conciseness, appropriateness, and accessibility. Much rural development research extends beyond the agricultural institutions and the clients with whom they traditionally have dealt. Policymaking and information systems often do not get properly linked. The most effective policy research has focused on specific programs or policy decisions. Meanwhile, university research can contribute to policymaking because the university has freedom to evaluate Federal programs, can tap alternative disciplines and data bases, and has organizational flexibility. Daft concludes that policymakers and researchers alike need to recognize the limits of knowledge in current rural development research.

Huie recognizes that local research and information needs must be tailored to needs and interests of elected officials, program directors, policymakers, or the general public. Information may be used to develop a consensus or to analyze a problem. Three stages are helpful: (a) clarifying the problem, (b) listing major alternatives, and (c) analyzing consequences of each alternative.

Brown recognizes if policy research is to be relevant, values will enter into the process. In the choice of the problem researched, a norm by which behavior or conditions are deemed inadequate must be established. One must then decide who is entitled to satisfaction of needs and who ought to provide the resources to meet those needs. Brown suggests the advocacy model used in court proceedings as one way to deal with values, but he also recognizes that, with unequal resources of contend-

ing groups, some values may not be adequately presented.

Researchers in Ohio report on their study of provision of adequate fire protection. How much protection should be provided? Most answers were based on available inputs. But how much is enough when some losses will result despite the degree of protection available? The professional standards of the American Insurance Institute schedule specified adequacy levels for services that are subjective and do not measure outputs.

Eberts and Sismondo show how five broad classes of social science research relate to policy research. They point to a series of relationships in the research process and to complexities requiring increasingly more data. One regional research committee discovered that its model required data not readily available. For other models, secondary data were often unavailable. Some data did not measure what the model required. As results can be no better than the weakest data set, the complex model gave results that appeared more impressive than was warranted. Discussion has centered on improving data, mainly primary data. Little recognition has been given to developing secondary data better suited to needs or to improving current data sets.

Hickman and Warren discuss alternative data sources and collection methods. They briefly summarize the strengths and weaknesses of alternative field collection methods for primary data.

Brooks discusses public opinion surveys, fully recognizing their strengths and weaknesses. One problem is that people may not know enough to respond intelligently.

Rural transportation problems require multidisciplinary team work. Richards and others indicate problems

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In many institutions, the separation of research and extension creates a barrier which guarantees communication failure.

of identifying regional socio-economic characteristics and regional transportation conditions. There are difficulties in eliciting value responses on transportation needs from residents of an area and relating those responses to current conditions. Yet their experience may be useful to others.

Land use, inevitably related to policy problems, often determines the location of social problems. Libby and Shelton point out that people live in the short run; people find it difficult to act when failing to do so has serious longrun consequences. Libby and Shelton recognize that decisions by researchers must be made quickly, although a professor-graduate student research team may move slowly. An alternate model, a senior researcher-fulltime research associate, has proved successful in many research efforts, especially "contract" research.

Mikes discusses feasibility studies but leaves unanswered the problem

of most public agencies—which studies should be undertaken? Universities might well conduct such studies with costs partially covered by a "contract" with the appropriate planning agency.

Gathering and disseminating appropriate information to each group of clients for public policy research is essential. Moe lists 10 factors that impede communication and 6 critical factors that facilitate dissemination of knowledge. One example of successful research is the Northeast regional study on agricultural labor. According to the client, "It is a rare occurrence when results of research conducted by the academic world bear such close and timely relationship to legislative proposals of the administration." Regional centers should have a key role in improving communication between researchers and their clients.

This reviewer concurs with Moe's list of functions that need strength-

ening. Yet Moe fails to point out that, in many institutions, the separation of research and extension creates a barrier which guarantees communication failure. As the total university becomes involved in some problems, a new commitment by engineering, education, medical, and law faculties will be needed to provide multidisciplinary research and communication.

The problem of how to do public policy research has not yet been solved; multidisciplinary research can help to deal with complex problems. The entire university probably has a role here. Data problems will need more attention, and secondary sources may become more useful. Communication problems can be lessened with conscious effort. Ideas that are not operational should be abandoned. Most models need to be simplified. This reviewer feels that this book should be studied by all those involved in research and extension in the public sector.

In Earlier Issues

At first glance, data on food expenditures and income in the United States in the past 20 years indicate that a larger proportion of income has been spent for food in this postwar period of record high incomes than in less prosperous years. This is contrary to what one would expect on the basis of Engel's famous law . . . Engel's law is generally remembered as stating that families with higher incomes spend a smaller proportion of their incomes for such necessities as food than do families with smaller incomes. If that is true of individual families, should it not hold for national averages? Engel's law . . . applies under conditions that are relatively static . . . certain forces arising from the war (diverted) an unusually large proportion of . . . purchasing power to food . . . The shift of population from rural to urban areas and the . . . increased processing of food outside the home . . . are likely to have a lasting effect on the relationship of aggregate food expenditure to income.

Marguerite C. Burk
AER, Vol. III, No. 3, pp. 87, 97
July 1951

THE MERCHANTS OF GRAIN

Dan Morgan. Viking Press, New York 1979.

*Reviewed by Anne del Castillo**

Dan Morgan covered the Russian grain deal of 1974 for the *Washington Post*. His research, which resulted in a detailed investigation of five multinational grain companies, is presented in *The Merchants of Grain*, an intriguing account of the grain merchants and their corporate penetrations into the grain industry and trade. The book reveals a market whose structure and behavior belie traditional economic assumptions.

The book opens with a history of the critical role of grain merchants from antiquity to modern times. During the past 50 years, this role has been concentrated in the hands of five family companies. Morgan provides a comprehensive account of the personalities who conduct this high-volume trade, highlighting the maneuvers and negotiations which are ultimately reflected in the commodity prices flashed across the Chicago boards.

Morgan devotes several chapters to a detailed reporting of the recent series of "under-the-table" three-way deals involving the grain companies and the Soviet and American Governments. He relies on interviews of the companies' former and current employees and official and unofficial statements by persons in the U.S. Departments of Agriculture and State involved in these negotiations.

Morgan's presentation of the myriad arrangements among the U.S. Government, the grain companies, and recipient countries of food under U.S. P.L.-480 gives the reader a sense of the political leverage and financial magnitude of the U.S. aid program.

*The reviewer is an agricultural economist with the International Economics Division, ESCS.

The final chapter contains implications of this concentration of economic power and the world's reliance on these five companies to feed its population.

The unique structure of the world grain trade raises an interesting question for the agricultural economist. Is

In Earlier Issues

The textbooks on economic statistics with which this reviewer is familiar describe the solution of "normal equations" in terms of elementary methods with which high-school graduates are presumed to be familiar. Typically, the students work out a correlation problem on obsolete calculators, recording each individual cross-product, and finally solve the normal equations by the textbook method. At the end of this process, all but the most ardent have concluded that regression equations are prohibitively difficult to come by, and that "research" reports can be written more rapidly if the data are merely described and not analyzed.

Karl Fox
AER, Vol. IV, No. 2
April 1952, p. 61

the convention of assuming a perfectly competitive market, with a string of modifying conditions, the best way to understand and interpret the world grain market? Perhaps a more accurate market portrayal would result if an oligopolistic structure were applied.

International grain trade is an anomaly of the competitive market model. Competition is keen, yet there are only a few players. The difference between good and mediocre timing can be fatal. The structures of the major companies are textbook examples of vertical and horizontal integration. The grain companies are equipped to meet any market circumstances; depending upon price developments, they can shift instantly from exporting soybeans to processing and selling meal and oil. After decades of diligent business acquisitions and mergers, these powerful yet discrete companies control practically every facet of the marketing process, from inland transportation to storage to interoceanic shipping.

The book raises a significant point regarding the structure and behavior of the world grain market. Experts are asking whether the market requires more public regulation and supervision. While economists are studying the welfare implications of proposed structural revisions of the market, the grain companies are struggling to preserve their prerogatives. The failure of the grain negotiations intended to bring a degree of stability and order into the world wheat market represented a singular victory for the grain companies. Proposals for establishing a national grain board in the United States or creating a wheat exporter cartel threaten the power of the grain companies. Should these proposals gain momentum, the grain companies may well oppose them.

Economists will find this book well written and reasonably well researched. *Merchants of Grain* is recommended for anyone who wants to understand more about the complicated and dynamic world grain trade market.

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